Denoising of Multispectral Images via Nonlocal Groupwise Spectrum-PCA

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Abstract

We propose a new algorithm for multispectral image denoising. The algorithm is based on the state-of-the-art Block Matching 3-D filter. For each "reference" 3-D block of multispectral data (sub-array of pixels from spatial and spectral locations) we find similar 3-D blocks using block matching and group them together to form a set of 4-D groups of pixels in spatial (2-D), spectral (1-D) and "temporally matched" (1-D) directions. Each of these groups is transformed using 4-D separable transforms formed by a fixed 2-D transform in spatial coordinates, a fixed 1-D transform in "temporal" coordinate, and 1-D PCA transform in spectral coordinates. Denoising is performed by shrinking these 4-D spectral components, applying an inverse 4-D transform to obtain estimates for all 4-D blocks and aggregating all estimates together. The effectiveness of the proposed approach is demonstrated on the denoising of real images captured with multispectral camera.

Introduction

Multispectral (MS) images consist of spatial maps of intensity variations across a large number of spectral bands or wavelengths; alternatively, they can be thought of as a measurement of the spectrum of light transmitted or reflected from each spatial location in a scene. MS imaging is used in a variety of applications such as remote sensing, astronomical imaging, and fluorescence microscopy.

A naive approach to denoising of MS images assumes fusing/aggregation of the multispectral images denoised independently. An alternative way is to process the full set of the multispectral data jointly. This approach is a much more efficient and productive, potentially allowing to reveal details and features which are practically invisible in each of the spectrum components considered separately.

The block-matching and 3-D filtering (BM3D) algorithm [3] is currently one of the most powerful and effective image denoising procedures [10], [9],[13]**.** It exploits a specific nonlocal image modeling through the procedures of *grouping* and *collaborative filtering*. Grouping finds mutually similar 2-D image blocks and stacks them together in 3-D arrays. Collaborative filtering produces individual estimates of all grouped blocks by filtering them jointly, through transform-domain shrinkage of the 3-D arrays (groups). In doing so, BM3D relies both on *nonlocal* and *local* characteristics of natural images, namely the abundance of mutually similar patches and the fact that image data is locally highly correlated. If these characteristics are verified, the group enjoys correlation in all three dimensions and a sparse representation of the true signal is obtained by applying a decorrelating 3-D transform on the group. The effectiveness of the subsequent shrinkage depends on the sparsity of the true signal; i.e. the true signal can be better separated from the noise when its energy is compactly represented in the 3-D transform domain.

In the case of multispectral images, additional sparsification of the image representation can be achieved by decorrelation of spectral components. For example, the Color-BM3D (CBM3D) algorithm [2, 3] designed for filtering natural RGB images follows the conventional approach based on a fixed luminance-chrominance color transformation applied to the whole RGB data and a particular special grouping-constraint to exploit the structural self-similarity shared by the three color components.

It must be however observed that while for natural RGB images the established opponent or YCbCr color transformations already provide near-optimal decorrelation of the color data, when one considers MS data at least two problems arise. First, there is no universal spectral decorrelating transform that can be considered optimal for generic MS data: as opposed to RGB imaging, MS imaging encompasses a wide range of imaging modalities and sensors technologies. Second, due to the potential high number of spectral components, a global spectral transformation may not be able to capture the heterogeneous correlation models between different components at different locations in the image.

This calls for a locally adaptive data-driven spectral decorrelation. A very natural approach to this problem, followed by many authors [11], [4], [12], [1], is to rely on the principal component analysis (PCA) to obtain a data-driven decorrelation of the spectral components. We especially wish to mention the work by Cagnazzo et al. [1], where the importance of localization of such PCA has been emphasized.

In this paper we propose an extension of the Color-BM3D algorithm for MS image denoising where spectral decorrelation is performed in a nonlocal spatially adaptive manner. Unlike in Color-BM3D, we process all spectral components jointly, considering 3-D image blocks and the correspondent 4-D groups. For each group, we calculate a PCA basis providing optimal spectral decorrelation. The final 4-D transform is performed as a separable composition of the spectral and 3-D spatial/interblock decorrelating transforms. We denote this new algorithm as MSPCA-BM3D.

Another important issue in MS image denoising is the high heterogeneity of the noise: multispectral images are typically corrupted by non-stationary noises with different noise levels for the different channels. This situation is obvious in case of aerial imagery, where the atmospheric disturbance appears only at certain wavelengths, or in CCD-based MS systems, where the extreme spectral bands are acquired near the operational limits of the sensor, thus where its efficiency is particularly low. Even when restricted to an individual spectral band, the noise cannot be assumed as additive identically and independently distributed (i.i.d.), because the sensor data is naturally heteroskedastic signal-dependent (often following Poissonian distributions). Thus, in practice, the noise variance depends both on the unknown signal and on the spectral band.

The applicability of MSPCA-BM3D to heteroskedastic data that follows different noise models across the different spec-

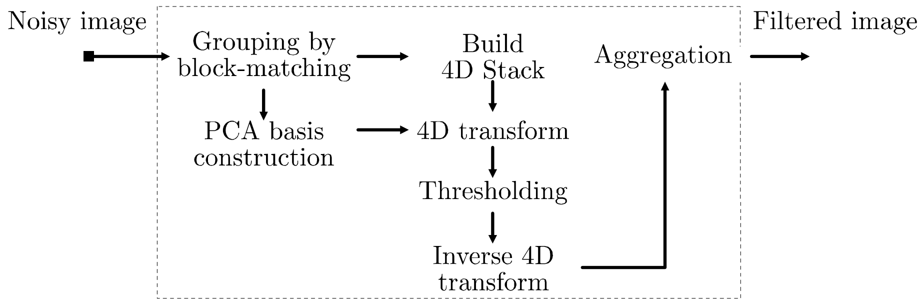

***Figure 1.** Flowchart of the proposed MSPCA-BM3D algorithm.*

tral bands is ensured by the noise-estimation and variance-stabilization framework developed in [7] and [6]. In this way, we arrive to a denoising procedure which is entirely automatic and that can be applied to data without need of prior noise characterization.

We demonstrate the effectiveness of the proposed MSPCA-BM3D algorithm on images from the Multispectral database[1] [8], [5]. Each image in this database contains 31 spectral components taken in the wavelength range of 400-700 nm, at 10-nm steps. For a comparison we also provide results of Color-BM3D algorithm adapted for MS data, where the spectral decorrelation is performed through a global PCA decomposition.

Observation Model

Let x be a 2-D spatial coordinate defined on the image domain $X \subset \mathbb{Z} \times \mathbb{Z}$, $k \in \{1,...,K\}$ be an index specifying the spectral component, and $y(x,k) : X \times K \to \mathbb{R}$ the unknown original noise-free K-spectral image. We consider the following observation model

$$z(x,k) = y(x,k) + \sigma(y(x,k),k)\,\xi(x,k), \tag{1}$$

where $z(x,k)$ is the observed noisy image, $\xi(x,k) : X \times K \to \mathbb{R}$, $E\{\xi(x,k)\} = 0$, $\text{var}\{\xi(x,k)\} = 1$ are independent (both in x and k) random variables, and $\sigma(\cdot,k)$ is a deterministic function of y describing the dependence of the standard deviation of the noise from the signal.

In the following section we first present the denoising algorithm under the simplistic assumptions of additive white Gaussian noise (AWGN) for which

$$\sigma(y(x,k))\,\xi(x,k) = \mathcal{N}\left(0,\sigma_0^2\right).$$

Further, we show how the general model given by (1) can be transformed to the AWGN case through variance stabilization.

MSPCA-BM3D Algorithm

The MSPCA-BM3D algorithm can be interpreted as an extension of the BM3D algorithm from 2-D to 3-D imaging. Detailed description of BM3D algorithm for 2-D imaging can be found in [3]. Here we outline the key steps of the proposed algorithm and pay special attention to the main contribution of this paper: the nonlocal PCA spectral decorrelation procedure.

It is assumed that a multispectral image $z(x,k)$ is represented as a 3-D array, where sections across the third dimension are 2-D images of the individual spectral components $z(\cdot,k)$. We define 3-D blocks as a subarrays of size $N_s \times N_s \times K$, where N_s and K are respectively spatial and spectral sizes of the block. We say that the block is located at x_0, if x_0 is the coordinate of left upper edge of the 3-D block.

[1] http://www2.cmp.uea.ac.uk/Research/compvis/MultiSpectralDB.htm

Algorithm outline

For each spatial position x_0 in the image domain X, select the corresponding noisy 3-D block as the reference one. For each reference block perform the following steps:

1. Using block matching, find 3-D blocks similar to the reference one and stack them into a 4-D array (group).
2. Using PCA, find an orthonormal transform providing optimal spectral decorrelation for the group.
3. Apply a 4-D transform to the formed array by subsequently applying: a) spectral decorrelating transform along the third (spectral) dimension, b) 2-D spatial decorrelating transform (e.g., DCT or wavelet) along the first and second dimensions, c) 1-D orthogonal transform along the fourth dimension to perform interblock decorrelation.
4. Denoise the data by shrinkage (hard thresholding or empirical Wiener filtering) of the obtained 4-D transform coefficients.
5. Apply the inverse 4-D transformation to obtain estimates for all grouped blocks.
6. Return the obtained block estimates to their original locations.

Compute the estimate of the true image by weighted averaging of all obtained blockwise estimates that are overlapping.

The diagram of the algorithm is presented in Fig. 1.

Nonlocal PCA spectral decorrelation

The input of Step 2 is the group of N_{gr} blocks of $N_s \times N_s \times K$ size. For each spatial location x_0 of each block we extract the corresponding spectral values $z(x_0,\cdot)$ and put them into a 1-D column vector $\vec{v}_i = [\; z(x_0,1) \quad z(x_0,2) \quad \ldots \quad z(x_0,K) \;]^T, i = 1,\ldots,N_{\text{total}}$, where $N_{\text{total}} = N_s \times N_s \times N_{gr}$ is the total number of such vectors. A $K \times K$ sample second-moment matrix is then computed as

$$C = [\; \vec{v}_1 \quad \vec{v}_2 \quad \ldots \quad \vec{v}_{N_{\text{total}}} \;][\; \vec{v}_1 \quad \vec{v}_2 \quad \ldots \quad \vec{v}_{N_{\text{total}}} \;]^T \tag{2}$$

and subsequently its eigenvalue decomposition yields

$$C = USU^T$$

where U is orthonormal matrix and S is a diagonal matrix containing eigenvalues ordered by magnitude.

The matrix U defines the PCA transformation for decorrelation of the spectral components of the blocks in the group.

Two-stage implementation

Similarly to [3] and [2], the above algorithm is implemented as a two-stage procedure. On the first stage, the shrinkage is performed by hard thresholding and the search for similar blocks is performed within the noisy image. On the second stage, we utilize the estimate image from first stage in the following manner:

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- the search for similar blocks is done within the estimate image,
- the shrinkage is performed by empirical Wiener filtering.

The improvement contributed by the second stage can be justified as follows. Because the noise has been attenuated in the filtered images, the block-matching operations can be produced more accurately. It results in sparser representations of the 4-D group spectra. In addition, the empirical Wiener filtering is much more effective than hard thresholding when the output of the first stage is used as reference signal in the empirical Wiener filter.

Denoising in the case of general noise model

The algorithm described above cannot be directly applied to data given by the general model (1), where the noise variance is signal dependent and varies across the spectral components. To overcome this problem we follow the variance-stabilization scheme developed in [6].

First, for each spectral component k, we estimate a standard-deviation curve $\sigma(\cdot,k)$ as a function of the image intensity. Second, for each such curve a specific (nonparametric) variance-stabilizing transformation is derived. Applying these transformations to the corresponding spectral components gives a transformed MS image where the noise can be treated as homoskedastic. Then, the MSPCA-BM3D algorithm proposed for homoskedastic noise is applicable. After denoising, the respective inverse variance-stabilizing transformation and bias-compensation procedures are applied to produce the final image estimate.

Note that for the purpose of this work, the effect of possible clipping discussed in [6] has been ignored.

Experiments

We demonstrate the effectiveness of the proposed MSPCA-BM3D algorithm on images from the Multispectral database[2] [8], [5]. Each image in this database contains 31 spectral components taken in the wavelength range of 400-700 nm, at 10-nm steps. Not going into the details of the acquisition system used to obtain these images, we just mention that the spectral components are finally recorded with a CCD sensor. This allows us to use the CCD/CMOS sensor noise model [7]:

$$\sigma(y(x,k),k) = \sqrt{a_k y(x,k) + b_k},\ k = 1,\dots,K$$

where $a_k \in \mathbb{R}^+$ and $b_k \in \mathbb{R}$ are some constants depending on the sensor's specific characteristics and on the particular acquisition settings.

For each spectral component, the parameters a_k and b_k are estimated and the homomorphic transformations for variance-stabilization and its inversion (including bias-compensation) are produced using methods from [7] and [6], as implemented in the ClipPoisGaus Toolbox[3].

To provide a comparison, we also performed denoising using the Color-BM3D algorithm adapted for MS data, where the spectral decorrelation is obtained through a global PCA decomposition. In Fig. 2 and Fig. 3 we show results obtained by both methods, together with the original noisy images. We can see that the nonlocal groupwise spectral decorrelation indeed allows to obtain better results, revealing details that is not possible to restore by global decorrelation. In particular this is visible on the first, most noisy, spectral component.

[2] http://www2.cmp.uea.ac.uk/Research/compvis/MultiSpectralDB.htm
[3] http://www.cs.tut.fi/~foi/sensornoise.html

Conclusions

We have introduced a new algorithm for multispectral image denoising. Following the nonlocal image processing paradigm, a spatially adaptive spectral decorrelation is performed for each group of similar bocks. Thanks to the grouping, the PCA transform can be calculated robustly, directly from the noisy image. Effective spectral decorrelation allows to achieve higher sparsification of the data, which results in better denoising. Experiments show superiority of the proposed approach over the method using global spectral decorrelation.

Acknowledgments

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Authors' Biographies

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Karen Egiazarian received the M.Sc. degree in mathematics from Yerevan State University in 1981, the Ph.D. degree in physics and mathematics from Moscow State University, Moscow, Russia, in 1986, and the D.Tech. degree from the Tampere University of Technology, Tampere, Finland, in 1994. He has been Senior Researcher with the Department of Digital Signal Processing, Institute of Information Problems and Automation, National Academy of Sciences of Armenia. Since 1999 he is a Professor in Department of Signal Processing, Tampere University of Technology, Finland, leading the Transforms and Spectral Methods group.

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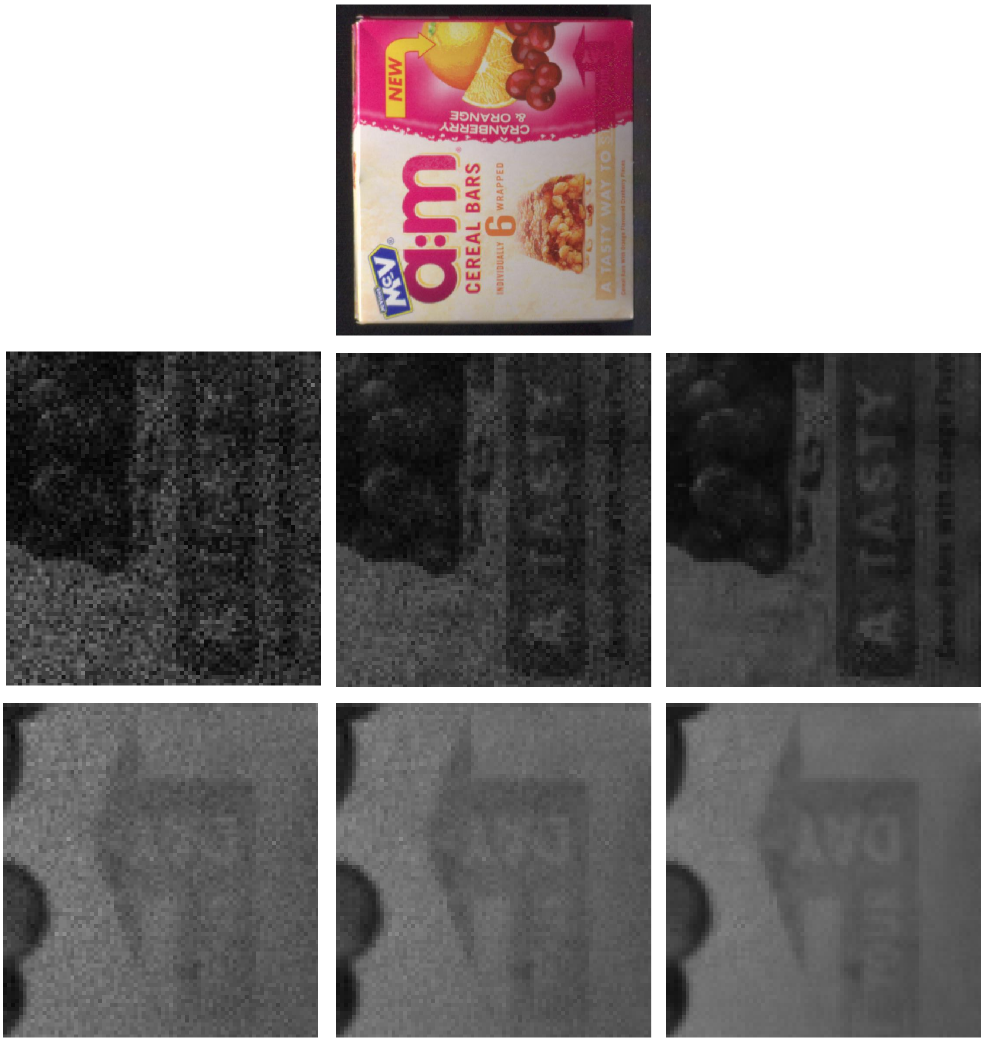

Figure 2. *Results of multispectral image denoising of the test image number 12 from the database [8]. From top to bottom: MS image (sRGB values rendered under a neutral daylight, D65), fragment of the 1st spectral component, different fragment of 31st spectral component. From left to right: noisy image, denoised by multispectral modification of CBM3D and denoised by proposed algorithm.*

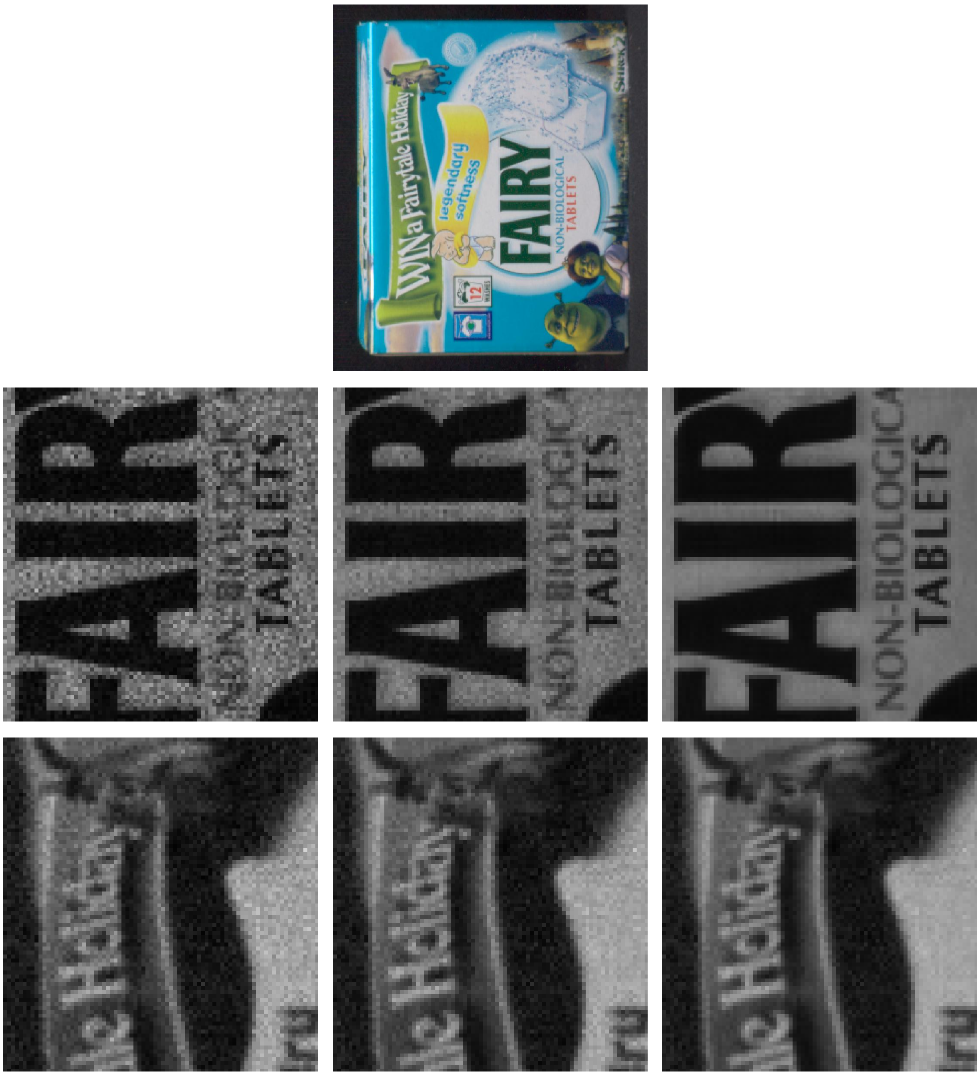

Figure 3. *Results of multispectral image denoising of the test image number 18 from the database [8]. From top to bottom: MS image (sRGB values rendered under a neutral daylight, D65), fragment of the 1st spectral component, different fragment of 31st spectral component. From left to right: noisy image, denoised by multispectral modification of CBM3D and denoised by proposed algorithm.*

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