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Image Denoising Using CSR

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Abstract

In this paper, we present a variational framework for unifying the above two views and propose a new denoising algorithm built upon clustering based sparse representation (CSR). Inspired by the success of l_1-optimization, we have formulated a double-header l_1-optimization problem where the regularization involves both dictionary learning and structural structuring.

Index Terms *- Sparse representation, clustering, PCA, LPG & denoising.*

1. Introduction

There have been two complementary views toward the regularization of image denoising problems: local vs. non-local. In the local view, a signal $\vec{x}$ £ R^n can be decomposed with respect to a collection of *n*-dimensional basis vectors in the hilbert space (also-called dictionary) **Φ** £ R^{n*m}, namely $\vec{x}_{n*1} = \mathbf{\Phi}_{n*m*} \vec{\alpha}_{m*1}$ where $\vec{\alpha}$ denotes the vector of weights. The sparsity of α can be characterized by its l_0-norm (non convex) or computationally more tractable l_1 norm [4]. This line of research has led to both construction of basis functions (e.g., ridgelet, contourlets) and adaptive learning of dictionary (e.g., K-SVD [5], stochastic approximation [6]). In the non local view, natural images contain self-repeating patterns. Exploiting the self-similarity of overlapping patches has led to a flurry of nonlocal image denoising algorithms - e.g., nonlocal mean [7], BM3D [8],

In this paper, we achieve the above objective by proposing a new image model called clustering-based sparse representation [9-10]. The basic idea behind our CSR model is to treat the local and nonlocal sparsity constraints (associated with dictionary learning and structural clustering respectively) as peers and incorporate them into a unified variational framework [1].

2. LPG-PCAbased denoising

In the m x n dataset matrix X_v, each component x_v^k, k=1,2,..,m, of the vector variable x_v has n samples. Denote by X_v^k the row vector containing the n samples of X_v^k. Then the data set X_v can be represented as $X_v = [(X_1^v)^T \ldots (X_m^v)^T]^T$. Similarly, we have $X = [X_1^T \ldots X_m^T]^T$, where X_k is the row vector containing the n samples of X_k, and $X_V = X+V$, where $V = [V_1^T \ldots V_m^T]$ is the dataset of noise variable t and V_k is the row sample vector of vk [2-3].

PCA is a classical de- correlation technique in statistical signal processing and it is pervasively used in pattern recognition and dimensionality reduction, etc. By transforming the original dataset into PCA domain and preserving only the several most significant principal components, the noise and trivial information can be removed.

In LPG-PCA, we model a pixel and its nearest neighbors as a vector variable. The training samples of this variable are selected by grouping the pixels with similar local spatial structures to the underlying one in the local window. With such an LPG procedure, the local statistics of the variables can be accurately computed so that the image edge structures can be well preserved after shrinkage in the PCA domain for noise removal.

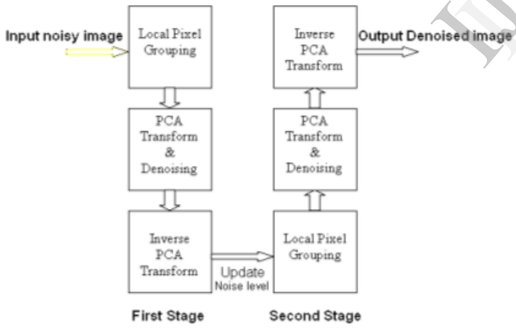

Figure -1: PCA-LPG algorithm

3. Clustering-based sparse representation (CSR) Model

Following the notation used in [4], we first establish the connection between an image $\mathbf{X}$ and the set of sparse coefficients $\alpha = \{\vec{\alpha}_i\}$ (so-called sparse land model). Let $\mathbf{x}_i$ denote a patch extracted from $\mathbf{X}$ at the spatial location i; then we have

$$\mathbf{x}_i = \mathbf{R}_i\mathbf{X} \quad \ldots(1)$$

where $\mathbf{R}_i$ denotes a rectangular windowing operator. Note that when overlapping is allowed, such patch-based representation is highly redundant and the recovery of $\mathbf{X}$ from $\{\mathbf{x}_i\}$ becomes an over-determined system. It is straightforward to obtain the following Least-Square solution

$$\mathbf{X} = (\sum_i \mathbf{R}_i^T \mathbf{R}_i)^{-1}(\sum_i \mathbf{R}_i^T \mathbf{x}_i)\ldots(2)$$

which is nothing but an abstraction of the strategy of averaging overlapped patches. Meantime, for a given dictionary, each patch is related to its sparse coefficients $\{\vec{\alpha}_i\}$ by

$$\mathbf{x}_i = \Phi\alpha_i\ldots(3)$$

substituting Eq. (3) into Eq. (2), we obtain

$$\mathbf{X} = \mathbf{D}\,\vec{\alpha} .= (\sum_i \mathbf{R}^T_i \mathbf{R}_i)^{-1}(\sum_i \mathbf{R}^T_i\, \Phi\alpha_i)$$

where $\mathbf{D}$ is the operator dual to $\mathbf{R}$ (reconstructing image from sparse coefficients).

CSR Algorithm

1. Initialization: $X^\wedge = Y$;
2. Outer loop (dictionary learning):
   for $i = 1, 2\ldots I$
   - update Φ via kmeans and PCA;
3. Inner loop (structural clustering):
   for $j = 1, 2\ldots J$
   - Iterative regularization:
     $X^\sim = X^\wedge + \delta(Y - X^\wedge)$;
   - Regularization parameter update:
     obtain new estimate of τ_1, τ_2;
   - Centroid estimate update:
     obtain new estimate of $\vec{\beta}_k$'s via kNN clustering;
   - Image estimate update:
     obtain new estimate of X by
     $X^\wedge = D \circ S \circ RX^\sim$;

TABLE - 1: Comparison of two stage LPG based PCA and CSR algorithms for standard images.

	PCA-LPG				CSR	
	PSNR1	PSNR2	SSIM1	SSIM2	PSNR	SSIM
MONARCH.TIF	29.6746	30.0384	0.8779	0.9145	30.62	0.9185
HOUSE.TIF	32.2187	33.0758	0.8098	0.8676	33.86	0.8737
LENA.TIF	30.2040	30.5415	0.8448	0.8765	30.93	0.8771
CAMERAMAN.TIF	29.5114	29.7184	0.7980	0.8765	30.45	0.8721
MAN.TIF	32.6249	33.6477	0.8695	0.9345	34.83	0.9444
PEPPER.TIF	30.1947	30.5252	0.8370	0.8743	31.19	0.8829
AVERAGE	**30.7380**	**31.2578**	**0.8395**	**0.8906**	**31.98**	**0.8947**

TABLE - 2: Comparison of denoising algorithms (PCA-LPG & CSR) for different images with different sigma values.

		SIGMA=20			SIGMA=10		
ALGORITHAM→		PCA-LPG		CSR	PCA-LPG		CSR
IMAGE ↓	PSNR →	PSNR1	PSNR2	PSNR	PSNR1	PSNR2	PSNR
MONARCH.TIF		29.6746	30.0384	30.62	33.8322	34.0698	34.44
HOUSE.TIF		32.2187	33.0758	33.86	35.8879	36.1184	36.83
LENA.TIF		30.2040	30.5415	30.93	34.1299	34.2963	34.48
CAMERAMAN.TIF		29.5114	29.7184	30.45	33.5149	33.6141	34.05
MAN.TIF		32.6249	33.6477	34.83	37.3540	38.2663	39.48
PEPPER.TIF		30.1947	30.5252	31.19	33.9829	34.0773	34.65
AVERAGE		**30.7380**	**31.2578**	**31.98**	**34.7836**	**35.0737**	**35.65**

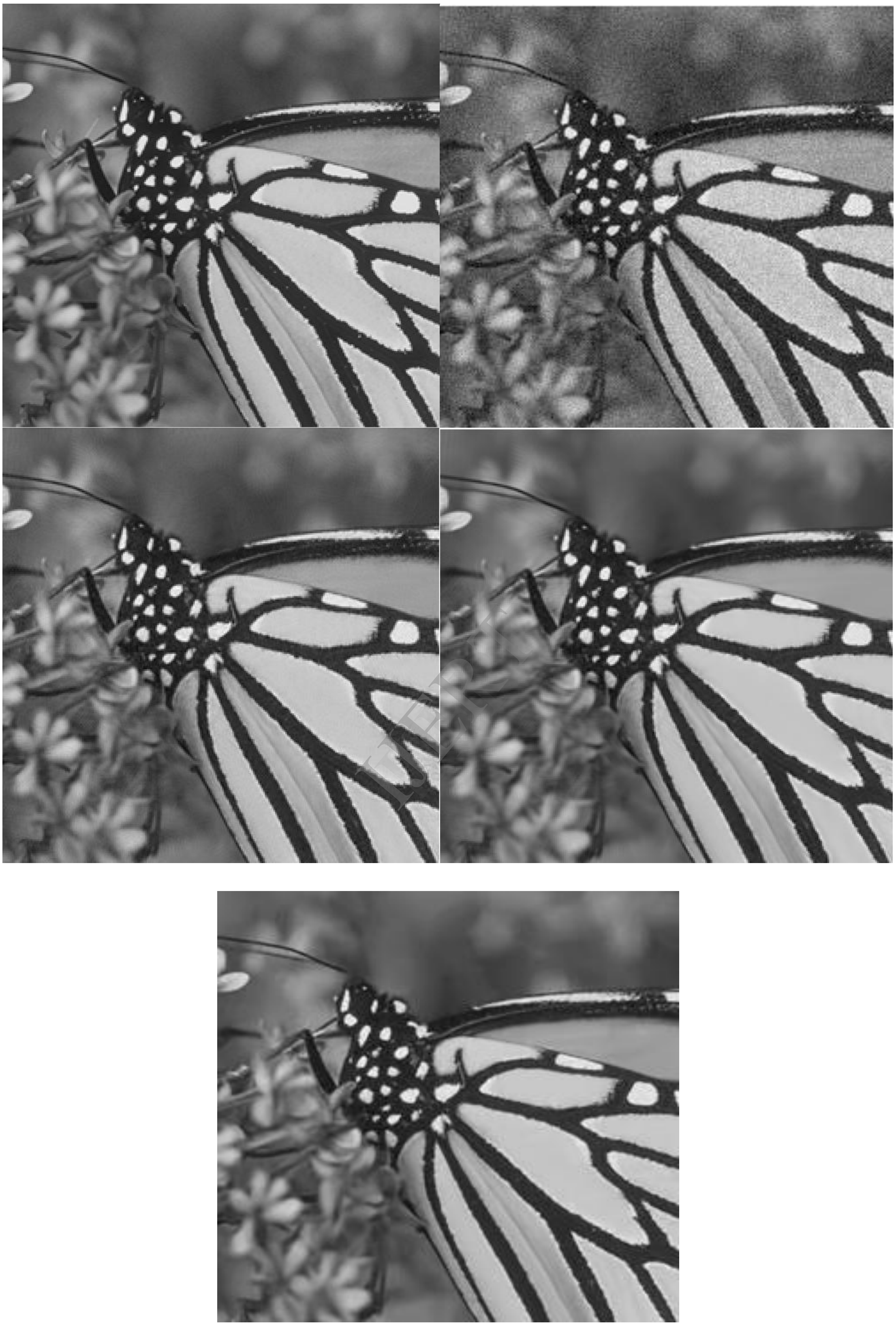

FIGURE - 2: Top left: Original image, top right: Noised image, middle left: Output of 1st stage of PCA-LPG algorithm, middle right: Output of 2nd stage of PCA-LPG algorithm & bottom: De-noised image with CSR algorithm.

FIGURE - 3: De-noised images with PCA-LPG algorithm.
(Top left: Peppers.tif, top right: Monarch.tif, middle left: Lena.tif, middle right: Man.tif, bottom left: House.tif & bottom right: Cameraman.tif)

FIGURE - 4: De-noised images with CSR algorithm.
(Top left: Peppers.tif, top right: Monarch.tif, middle left: Lena.tif, middle right: Man.tif, bottom left: House.tif & bottom right: Cameraman.tif)

4.Experimental Results& Conclusion

We have considered the six standard images for our discussion. In table-1, we compared PSNR values and SSIM values of denoised images with two algorithms LPG based PCA and PCA based CSR. In table-2, we compared PSNR values for the same images with different sigma values with the same algorithms. From our results we can clear say that the output of 1st stage of PCA-LPG is lesser than 2nd stage of PCA-LPG. And the PSNR value that we got in CSR algorithm is more than the value of the PSNR values of PCA-LPG values.

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