IMAGE DENOISING WITH SHAPE-ADAPTIVE PRINCIPAL COMPONENT ANALYSIS

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INTRODUCTION

We propose an image denoising method that exploits:

- nonlocal image-modeling (concept originating from [Buades2005]),
- shape-adaptive filtering (proposed in [Foi2007]), and
- principal component analysis (PCA).

Noise is attenuated by shrinkage in a transform domain; its effectiveness depends on the ability of the transform to sparsely represent true-image data. In our previous works [Dabov2007,2008] we have addressed the problem of increasing the sparsity by employing non-local modeling by grouping similar image patches in 3-D groups and by using adaptive-shape neighborhoods [Dabov2008] instead of rectangular ones. In this work, we extend these methods by exploiting data-adaptive Principal Component Analysis (PCA) on adaptive-shape neighborhoods as part of the employed 3-D transform.

PROPOSED METHOD

The proposed method (illustrated in Figure 1) works as follows. An input noisy image is processed in a raster scan, where at each pixel the following is done.

1. Group together square image blocks that are similar to the block centered at the current pixel.
2. Obtain the anisotropic neighborhood at the current pixel using 8-directional LPA-ICI [Foi2007]. Apply its shape on each of the grouped blocks, producing a group of adaptive-shape neighborhoods.
3. Use this group as training data for computing Shape-Adaptive PCA. That is, a PCA basis is obtained by eigenvalue decomposition of the empirical second-moment matrix estimated from the group of similar adaptive-shape neighborhoods. As principal components (PC), we keep only the eigenvectors whose corresponding eigenvalues are greater than a threshold proportional to the noise variance. The overall 3-D transform is a separable composition of the PCA (applied on each image patch) and a fixed orthogonal 1-D transform in the third dimension.
4. Apply the 3-D transform on a group of adaptive-shape neighborhoods.
5. Attenuate noise by hard-thresholding or empirical Wiener filtering.
6. Apply the inverse 3-D transform to obtain filtered neighborhoods, which are then returned to their original locations and aggregated in case of overlapping.

We propose to do the above steps in three iterations, where hard-thresholding is used in the first two iterations and empirical Wiener filtering is used in the third. Additionally, in the second and in the third iterations, the search for similar blocks and the PCA computation are performed on the estimated images from the preceding iterations.

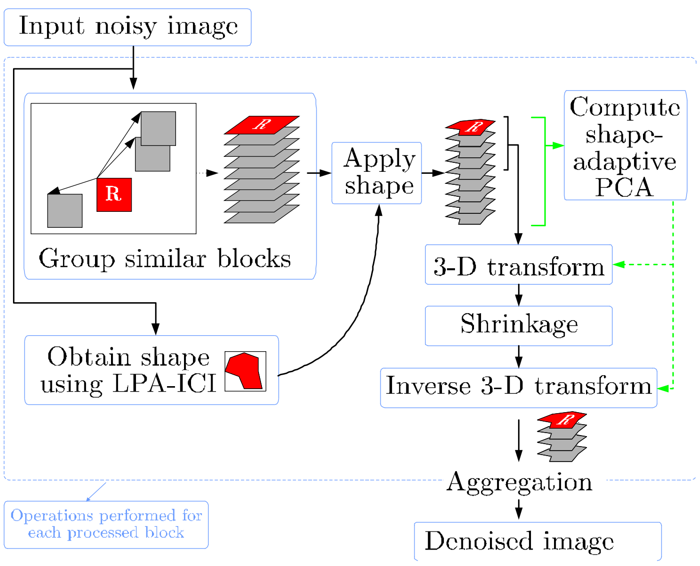

Fig. 1. Flowchart of the proposed method.

CONCLUSIONS AND FUTURE WORK

- State-of-the-art results in terms of both denoising and detail preservation.
- Relatively high complexity (due to application of PCA locally).
- Future work involves parameter optimization and application of the eigenvalues in the shrinkage itself (rather than trimming the number of PCs based on the eigenvalue magnitudes)

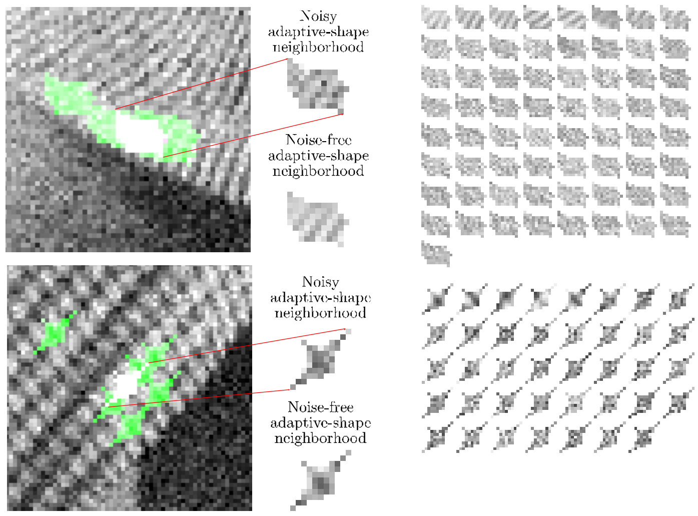

Fig. 2. Illustration of the PCs (listed by decreasing eigenvalue magnitude) for two adaptive-shape neighborhoods. The green overlay shows the grouped similar neighborhoods.

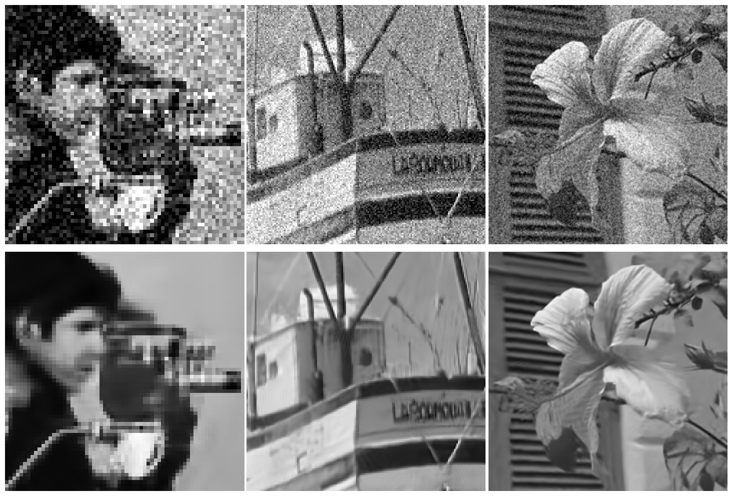

Fig. 3. Fragments of noisy (st. dev. 25) and denoised images.

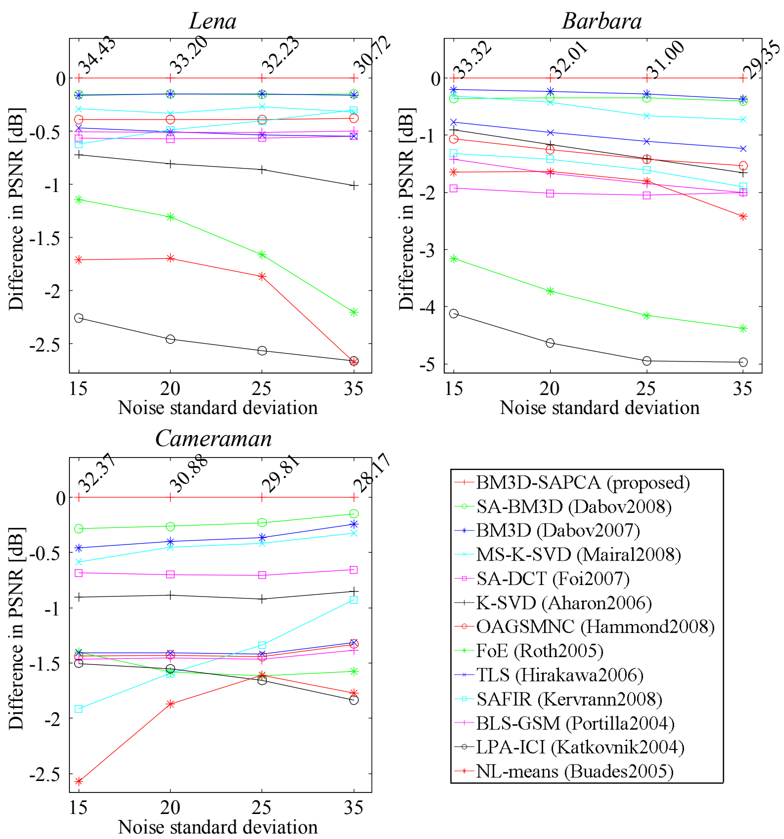

Fig. 4. PSNR comparison with other methods.