Journal of Visual Communication and Image Representation 50 (2018) 111–122

Contents lists available at ScienceDirect

Journal of Visual Communication and Image Representation

journal homepage: www.elsevier.com/locate/jvci

Principal component dictionary-based patch grouping for image denoising☆

Shoukui Yao*, Yi Chang, Xiaojuan Qin, Yaozong Zhang, Tianxu Zhang

National Key Laboratory of Science and Technology on Multispectral Information Processing, School of Automation, Huazhong University of Science and Technology, Wuhan, China

A R T I C L E I N F O

Keywords:
Nonlocal self-similarity
Transform-domain
External knowledge
Image denoising

A B S T R A C T

Improving denoising algorithms based on nonlocal self-similarity (NSS) to cope with increasing noise levels has become difficult. This is primarily because of difficulty in accurately grouping similar image patches solely on original spatial-domain of noisy images. To solve this problem, we propose to group similar patches on transform-domain learned from clean natural images. In this paper, we introduce a denoising algorithm comprising principal component dictionary (PCD)-based patch grouping and a low-rank approximation process. In the proposed algorithm, PCD learns from clean natural images and uses the knowledge gained to guide similar patches grouping results in noisy images. Patch grouping is directly implemented on PCD-based transform-domain. And, external knowledge and internal NSS prior are used jointly for image denoising. The results of experiments conducted indicate that the proposed denoising algorithm outperforms several state-of-the-art denoising algorithms, especially in heavy noise conditions.

1. Introduction

As rapid progress of digital imaging devices, image resolution increases quickly. Higher resolution images are more easily contaminated by noise. Therefore, there are increasing requirements of better denoising algorithms. Given a noisy image $\boldsymbol{y} \in \mathbb{R}^{n\times 1}$, image denoising can be generally formulated by $\boldsymbol{y} = \boldsymbol{x} + \boldsymbol{v}$, where $\boldsymbol{x} \in \mathbb{R}^{n\times 1}$ is the latent clean image, $\boldsymbol{v} \in \mathbb{R}^{n\times 1}$ is the additive white Gaussian noise, and $\boldsymbol{n}$ is the number of pixels in the image. As a classical problem in low-level vision, image denoising is an active topic [1–17]. Numerous denoising algorithms have been developed to date. Existing techniques can be roughly divided into two categories: conventional local prior-based methods and nonlocal self-similarity (NSS)-based methods. Conventional local prior-based methods include wavelet shrinkage based methods [1–4], total variation based methods [5,6,12], and sparse representation based methods [7,8]. Because these methods only concentrate on local priors, their performances are limited.

Algorithms based on nonlocal self-similarity (NSS) prior, which uses the recurrence of small patches in natural images, have achieved great success [9,18–27]. Buades et al. [20] proposed the nonlocal means (NLM), which was the first method to explicitly exploit NSS for image denoising. NLM method estimated each pixel as the weighted average of all pixels in image. Inspired by the success of NLM method, Dabov et al. [21] proposed the "block matching" and 3D filtering (BM3D) method. They used "block matching" to search for similar patches in the image and grouped those patches into a 3D cube. The 3D filtering was realized by using three steps: 3-D transformation of a group, shrinkage of transform spectrum, and inverse 3-D transformation. BM3D algorithm becomes an image denoising benchmark. Mairal et al. [18] proposed the learned simultaneous sparse coding (LSSC) method by incorporating NSS and group sparse coding. They grouped similar patches and jointly decomposed the groups on subsets of learned dictionary. To improve the performance of sparse representation-based image restoration, Dong et al. [19] proposed the non-locally centralized sparse representation (NCSR) to reduce the sparse coding noise for image denoising. They exploited NSS to obtain good estimates of the sparse coding coefficients of the original image. Gu et al. [23] presented weighted nuclear norm minimization (WNNM) algorithm and applied it to image denoising by exploiting NSS. They have also achieved state-of-the-art image denoising performance. All of these algorithms adopted "block matching" to group similar patches. However, the performance of "block matching" decreases remarkably as noise levels increase. Fig. 1 shows the results of an experiment conducted using the "block matching" method, in which the red points are the centroids of the most similar patches. As shown in the figure, the error-matching rate of similar patches increases with the noise variance. The issue of how to group similar patches correctly in noisy images is an open problem.

"Block matching" is implemented on the original spatial-domain of noisy images. Because noise covers the evidence of similarity on the original spatial-domain, the performance of this method is limited. To

☆ This paper has been recommended for acceptance by Zicheng Liu.

* Corresponding author.
E-mail address: ysk2013@hust.edu.cn (S. Yao).

https://doi.org/10.1016/j.jvcir.2017.11.019
Received 24 May 2017; Received in revised form 19 September 2017; Accepted 20 November 2017
Available online 22 November 2017
1047-3203/

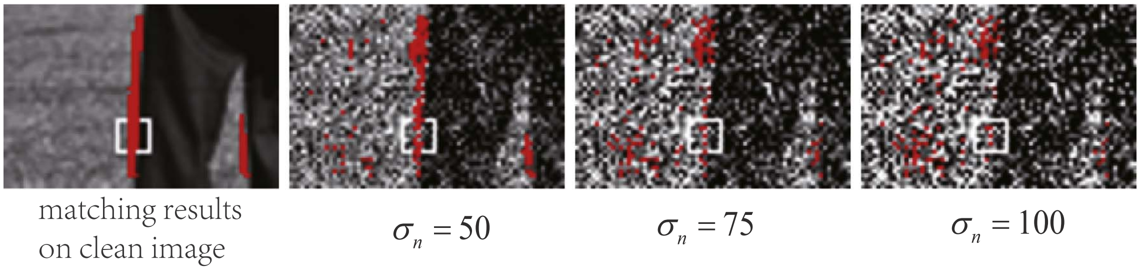

Fig. 1. Patch-matching results of the "block matching" method. White boxes denote reference patches; red points label the location of searched similar patches. The error-matching rate of similar patches increases with noise variance. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

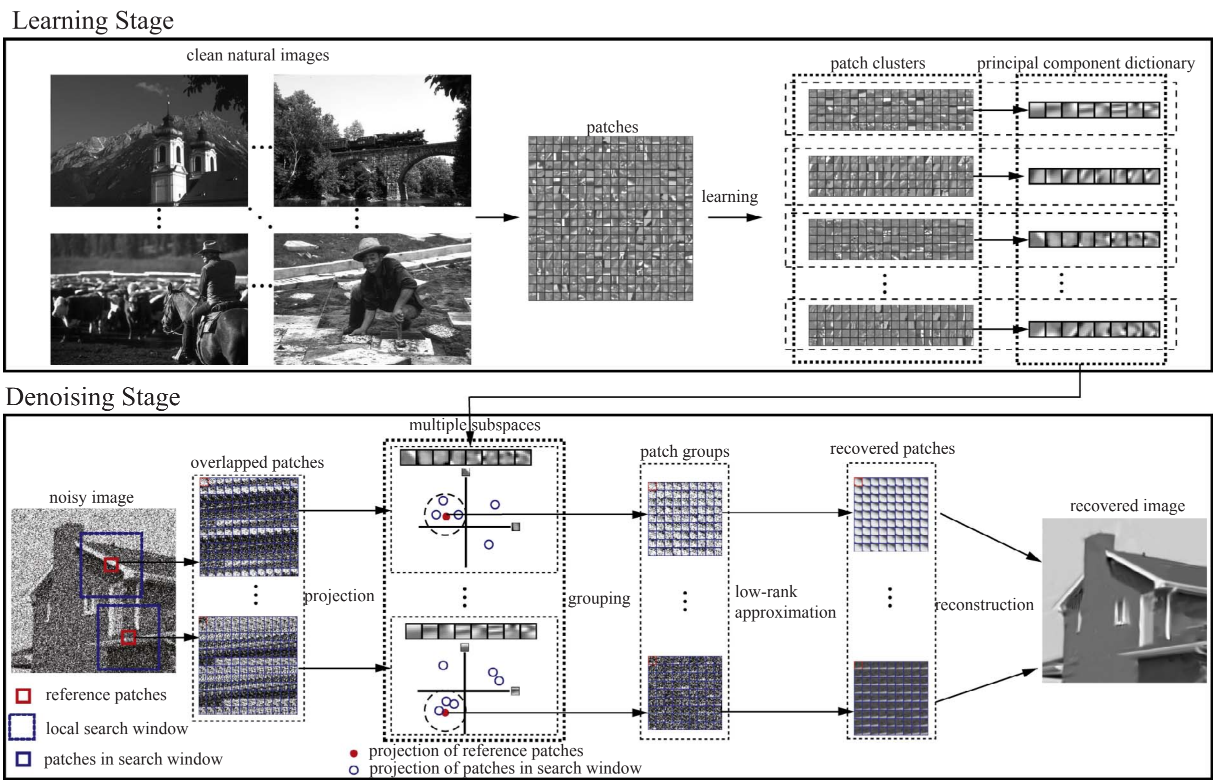

Fig. 2. Flowchart of the proposed denoising algorithm based on PCD. In the learning stage, PCD learns from clean natural images. In the denoising stage, noisy patches are projected onto the multiple subspaces constructed by PCD to estimate their principal components, which are then used as features to group similar patches. A low-rank approximation process is applied to the patch clusters for denoising.

solve this problem, we propose to group similar patches on transform-domain learned from clean natural images. On one hand, the original spatial-domain of noisy images is redundant. We hope to obtain more compact subspaces from transform-domain for more accurate image structure expression, so that patch grouping results can be promoted. On the other hand, structure information in noisy images has been contaminated by noise. We hope to enhance patch grouping results by using external clean image structure information. To achieve this goal, we learn principal component dictionary (PCD) from clean natural images, and use PCD to guide similar patches grouping. We introduce a denoising algorithm that combines PCD-based patches grouping with a low-rank approximation process. Fig. 2 presents a flowchart of the proposed denoising algorithm. As shown in the figure, PCD learns from clean natural images and constructs multiple subspaces. The eigen-vectors in the sub-dictionaries of PCD represent the directions of co-ordinate axes in multiple subspaces. Noisy patches are projected onto multiple subspaces to estimate their principal components. Patches are grouped on transform-domain by using the estimated principal com-ponents as features. The PCD-based grouping scheme is robust to noise. A low-rank approximation process is then applied to restore similar patches groups. Because patch grouping uses external knowledge from clean natural images and the low-rank approximation process exploits internal NSS prior from noisy images, external knowledge and internal NSS prior are simultaneously used in our proposed denoising algorithm. Experimental results show that our proposed algorithm outperforms many state-of-the-art denoising methods, especially in heavy noise conditions.

Chen et al. [28] proposed an external patch prior guided internal clustering algorithm. They learned Gaussian mixture models (GMMs) from clean images and used them to guide the clustering of noisy pat-ches, followed by a low-rank approximation process for image re-storation. However, their proposed patch grouping method is not good enough. GMM-based method cannot, in general, complete patches grouping through clustering of the patches all at once. Following their first clustering process, the number of patches in some classes was found to be too large. They, therefore, used the K-means algorithm to partition the larger classes, but the second clustering process imported errors.

Pre-process for better grouping has been used in some other NSS-based algorithms. BM3D algorithm adopted a two-stage denoising