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Two-step group-based adaptive soft-thresholding algorithm for image denoising

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ABSTRACT

Some approaches based on learning basis and self-similarities have shown powerful results apply to image denoising, reconstruction and some other classification tasks. Among these restoration techniques, BM3D and LASSC demonstrate amazing stability in dealing with natural images of different noise level. These methods make full use of nonlocal self-similarity and group sparsity. Taking advantage of the superiority, we propose a two-step group-based adaptive soft-thresholding algorithm for image denoising. We apply adaptive soft-thresholding to higher order singular value decomposition (HOSVD) and consider this operation as the first step, obtaining a basic estimate of the clean image. In the second step, denoising is also realized in the group-based framework and the final result is obtained by applying the basic estimate to the model which makes up of a *F*-norm fidelity term and an adaptive weighted nuclear norm regularization term. Compared with several state-of-the-art denoising methods, the proposed method requires less iterations and execution time. Experiment results demonstrate obvious improvement over BM3D and LASSC in PSNR value and visual effect.

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1. Introduction

One of the most important problems in image processing is the recovery of a corrupted image Y, which may be degraded by noise, blur, missing data. The goal is to reconstruct important structural features of the original image, such as large scale objects (smooth regions), edges (discontinuities) and textures (patterned small scale details). This problem is typically written as an inverse problem: given Y, find X which is a smooth approximation of Y in some sense. Specifically, we consider the problem of image denoising that decompose $Y = X + N$, where X is the real image and N is the residual assumed to be noise image. In the early work, the restored image is always assumed to be smooth or sparse under some prior knowledge, such as the gradient. A classical denoising model is the ROF model proposed by Rudin, Osher and Fatemi [1]. Although the ROF model is effective for edge-preserving, the recovered image usually suffers from the staircase border. After that, a lot of methods emerge to make up the drawback of the ROF model, such as the isotropy and anisotropic filtering [2]. However, there are two questions: firstly, the smooth assumptionof natural image is unreasonable; secondly, those methods handle the pixels one by one, ignoring the whole information in an image. This promotes greatly the development of the global denoising methods.

One of the early proposals is the nonlocal mean denoising [3], which explores the nonlocal self-similar nature of images. In the nonlocal view, natural images contain self-repeating patterns or say nonlocal self-similarity (NSS), allowing one to exploit similar structures around every reference patch. After that, more attentions were appealed to explore the superiority of the nonlocal operators and apply to several classical models [4,3,5–10]. Similar to the nonlocal-means filtering, the BM3D method [5] finds similar neighbors to every reference patch in an image (block matching), and then stacks them together into a 3D "group" and performs a collaborative filtering with a 3D transform (DFT and DCT) to filter the group. Finally, the final result is obtained by aggregating all the obtained 2D estimates.

Compared with fixed transforms, learned transform basis has been increasingly applied to image denoising [11–15]. During searching overlap similar neighbors one can get a linear expression of the original patch according to the level of similarity. Considering this, instead of using fixed basis (e.g., Fourier, wavelet and Gabor), one can use a dictionary learning from the statistics property of image features or patches. Unlike fixed basis, the learned dictionary is "overcomplete" which leads to more sparse representation

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of the image. Further studies on similar patch groups gained by NSS have shown that they are low-rank [16].

Next we give an introduction of four denoising methods LSSC [9], LASSC [17], WNNM [18], and the HOSVD denoising [19], which all use dictionary or basis learning from similar image patches or 3D groups. The LSSC method uses simultaneous sparse coding [20] to get the sparse coefficients of the similar patches on the learned dictionary. At the same time, the dictionary is updated by jointly projecting groups of similar patches to the subsets of the learned dictionary. Finally, the result is computed by the inverse transform. The LASSC method proposes a spatially adaptive iterative singular-value threshold (SAIST) algorithm and generalizes BayesShrink [21] to nonlocal models for image denoising. The threshold of LASSC is related to singular value and changes with iteration. The recent WNNM method applies nuclear norm as the regularization term instead of other norms to achieve the low-rank constraint of the image groups. In addition, the author assigns adaptive selected weights to the nuclear norm, which can improve the denoising performance. Very recently, in [19] the authors propose a novel denoising method called HOSVD denoising, with excellent results. Unlike the above three methods which treats image patches as vectors, the HOSVD denoising method works on 3D groups including matrix-based similar patches. The main feature of HOSVD denoising is that it uses basis by computing the higher order singular value decomposition (HOSVD) of the groups, which can be considered as learned dictionary. On color images, this method produces state-of-the-art results, especially at moderately high noise levels.

In this paper, based on the merits of the LASSC and the HOSVD denoising, we propose a two-step group-based denoising algorithm. In the first step, the proposed method produces a basic estimate of the clean image by dealing with 3D groups consisting of similar patches. Different from BM3D which uses fixed transform, we utilize learned dictionary HOSVD to filter the group. In addition, we apply adaptive soft-threshold to HOSVD to improve its performance. In the second step, we adopt the framework of WNNM to further denoise the image. Thanks to the first step, we can achieve higher quality grouping results and thus significantly reduces the iterative times and the execution time.

We introduce adaptive threshold to the transform coefficients which makes the denoising model be non-convex, thus the model is hard to solve directly with sub-gradient method since the derivation conditions are no longer satisfied. To overcome the difficulty, we use the methods [13] and [18] for the solution of the proposed model. Our contributions are two-fold. First, the proposed adaptive threshold is more reasonable then fixed threshold. Second, applying the basic estimate to the second step can reduce the iterative times and the execution time.

The paper is organized as follows. In Section 2, we make a brief introduction of the SAIST algorithm [17] and the HOSVD denoising method [19]. We elaborate our two-step adaptive soft-threshold algorithm in Section 3. The experiment results are presented in Section 4. In Section 5, we conclude this paper.

2. Background

In this section, we introduce the background of our method in two sides, one is the HOSVD denoising method used in the first step, other is the SAIST algorithm used in the second step.

2.1. The HOSVD denoising model

We now make a brief introduction of the HOSVD denoising [19]. In this paper, the author begins with applying matrix SVD to image denoising based on image patches in sliding window fashion. This method indeed performs some denoising but the performance is relatively poor. The reason is that the noise affects not only the singular values but also the singular vectors. Then, the author proposes the Nonlocal SVD denoising method, which works on groups with similar patches and estimates both singular values and singular vectors. This method produces excellent denoising results, however, it denoises every patch independently, whose good performance requires perfectly similarity between image patches which is not possible in practice. To this end, they propose the HOSVD denoising, whose idea is based on the joint filtering of similar image patches. Unlike BM3D, the HOSVD denoising method utilizes learned spatially adaptive bases computed from the HOSVD of the 3D groups and achieves further sparsity of the transform coefficients.

The HOSVD denoising method begins with the grouping procedure. Given a patch P from the noisy image, grouping looks for $K-1$ patches that are similar to P and groups them (including P) together into a 3D stack $\mathcal{Z} \in \mathbb{R}^{p\times p\times K}$. In the following denoising procedure, according to [22], the authors compute the HOSVD of $\mathcal{Z}$ that $\mathcal{Z} = S \times_1 U^{(1)} \times_2 U^{(2)} \times_3 U^{(3)}$, where $U^{(1)} \in \mathbb{R}^{p\times p}$, $U^{(2)} \in \mathbb{R}^{p\times p}$, $U^{(3)} \in \mathbb{R}^{K\times K}$ are orthonormal matrices, and S is a 3D coefficient array of size $p \times p \times K$. Then the group is filtered by applying a hard-thresholding to S and the threshold is picked to be $\sigma\sqrt{2\log p^2 K}$. Then the group estimate is obtained by performing the inverse transform. After doing the same thing to all the groups, finally, the basic estimate image X_{basic} is computed by aggregating all the obtained patch estimates. The above procedures form the first step of HOSVD denoising (HOSVD 1).

Similar to BM3D, the author also proposes a Wiener filter step (HOSVD 2) to improve the denoising performance. More precisely, HOSVD 2 performs grouping on X_{basic}, instead of Y, for a higher quality of the grouping result. Let $\mathcal{X}$ be a stack of similar patches from X_{basic} and $\mathcal{Y}$ be the corresponding stack from the noisy image Y. Assuming that the coefficients of $\mathcal{X}$ and $\mathcal{Y}$ under the learning bases of X_{basic} are denoted as $c_{\mathcal{X}}$ and $c_{\mathcal{Y}}$, respectively. The filtered coefficients $\hat{c_n}$ of $\mathcal{Y}$ are computed by $\hat{c_n} = \frac{c_{\mathcal{Y}} c_{\mathcal{X}}^2}{c_{\mathcal{X}}^2 + \sigma^2}$. It provides a more reasonable adaptive threshold than that in HOSVD 1 and demonstrates significantly improvement on the denoising result.

2.2. The SAIST algorithm

In the work [17], the authors propose a spatially adaptive iterative singular-value thresholding (SAIST) algorithm for image denoising and image completion. The idea of the SAIST algorithm is based on exploring the connection between the nonlocal-based methods and the low-rank-based methods. The authors propose a group-based model with a group sparsity regularizer $||\cdot||_{1,2}$ (pseudo-matrix norm) based on the SSC [9] model. The above method combines both nonlocal method and low-rank method in one model. Note that the SSC model assumes that the sparsely-coded patches are independent, which is unreasonable for natural images. By applying the pseudo-matrix norm to SSC, this model can overcome the defect of SSC and explore better the dependence of patches. Furthermore, the authors point out that the SVD formulation of the group can be interpreted in bilateral variance estimation perspective, which makes clear the relationship between the nonlocal methods and low-rank methods. In order to achieve spatial adaptivity, the authors utilize the deterministic annealing [23] and iterative regularization [24] to estimate the noise variance and signal variance under the framework of Bayesian analysis. Finally, they get the thresholding estimation based on the obtained results. Some details of the SAIST algorithm are given in the following.

The main idea of the iterative regularization method is to add the filtered noise back to the denoised image. The authors alternatively estimate the noise variance and signal variance while denoising.

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