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Joint image denoising using adaptive principal component analysis and self-similarity

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ABSTRACT

The non-local means (NLM) has attracted enormous interest in image denoising problem in recent years. In this paper, we propose an efficient joint denoising algorithm based on adaptive principal component analysis (PCA) and self-similarity that improves the predictability of pixel intensities in reconstructed images. The proposed algorithm consists of two successive steps without iteration: the low-rank approximation based on parallel analysis, and the collaborative filtering. First, for a pixel and its nearest neighbors, the training samples in a local search window are selected to form the similar patch group by the block matching method. Next, it is factorized by singular value decomposition (SVD), whose left and right orthogonal basis denote local and non-local image features, respectively. The adaptive PCA automatically chooses the local signal subspace dimensionality of the noisy similar patch group in the SVD domain by the refined parallel analysis with Monte Carlo simulation. Thus, image features can be well preserved after dimensionality reduction, and simultaneously the noise is almost eliminated. Then, after the inverse SVD transform, the denoised image is reconstructed from the aggregate filtered patches by the weighted average method. Finally, the collaborative Wiener filtering is used to further remove the noise. The experimental results validate its generality and effectiveness in a wide range of the noisy images. The proposed algorithm not only produces very promising denoising results that outperforms the state-of-the-art methods in most cases, but also adapts to a variety of noise levels.

1. Introduction

Image denoising is still a challenging problem in the fields of image processing and computer vision. It refers to the recovery of a digital image that has been contaminated by some types of noise, e.g., Gaussian noise, or Rician noise, while preserving image features such as the edges and the textures. The problem of image denoising [34,29] was first studied in 1970s. After the development of wavelet transform in late 1980s, many denoising methods based on wavelet transform and its variants have appeared in the literatures [13,39,6,17,40,35]. However, they often blur the sharp edges and smooth out the fine structures.

Since the non-local means (NLM) algorithm [5] was published by Buades et al., many more powerful denoising techniques have been proposed in the past several years [1,14,30,15,9,42,52,53,12,27,56,2,55,21,31]. After a brief review, there are two basic categories for image denoising approaches. One of them is the spatial filters, which can be further classified into linear filters and non-linear filters. Some of the recent popular linear spatial filters are bilateral filtering [38], Wiener filtering [18], NLM [5] and Total Least Squares (TLS) [23]. Furthermore, many variants of the NLM method [5] were also developed to improve its weight calculation, e.g., Stein's unbiased risk estimate (SURE) [43,36], the principle neighborhood dictionary (PND) [42] and the MMSE approach [28]. Similarly, the typical non-linear spatial filters are total variation regularization

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(TV) [37], Kernel Regression (KR) [41] and the diffusion filter [4]. The other category is transforming domain filtering methods, which can also be further divided into the non-data adaptive transforms including wavelet-based variants [40,35] and data adaptive transforms, such as K-SVD [1], BM3D [9], principal component analysis (PCA) [54,10] and independent component analysis (ICA) [8].

One main direction of these works is to find sparse representations of signals built on the globally or locally adaptive basis. Assuming that each image patch can be sparsely represented, K-SVD algorithm [1] and its variant [51] learn a sparse and redundant basis of image neighborhoods to remove noise. But they ignore the characteristics of the human visual perception that the edges and textures of the image contribute greatly to the subjective assessment of image quality. The KR method with recursive iterations proposed by Takeda et al. [41] has expensive computation, which is difficult to achieve real-time processing. He et al. [22] proposed an image denoising method using the adaptive thresholding scheme by singular value decomposition. However, its denoising performance depends on three free parameters, which are quite tricky and difficult to tune for optimal values. The patch-based PLPCA method [10] adopts the hard thresholding technique directly for the elements of the eigenvectors, whereas it also damages the sharp edges and the fine structures. Furthermore, its thresholding value is based on the known noise deviation. However, in fact, the noise deviation is unknown in most cases. To the best of our knowledge, the best existing state-of-the-art filtering methods are mostly based on the optimal Wiener filter [9] or equivalently Linear-Minimum Mean Squared Error (LMMSE) [54]. Although they have very good performance for reducing additive white Gaussian noise (AWGN) from the noisy image, they have not yet reached the limit of noise removal [7].

These denoising methods mentioned above have the drawback that while removing noise, they may also smooth the edges and the fine structures in the image. To mitigate this drawback, different from the existing denoising methods, we propose an advanced denoising algorithm based on adaptive principal component analysis and self-similarity (APCAS). The proposed algorithm consists of two successive steps without iteration: the low-rank approximation based on parallel analysis, and the collaborative filtering. The image self-similarity is exploited to construct similar patch groups. Parallel analysis is used to choose the signal dimensionality of the coefficients in the SVD domain of the similar patch group. This dimensionality reduction technique can adaptively determine the number of signal components in noisy environments. The low-rank approximation of the true image is employed to perform the empirical Wiener filtering to further reduce the noise. Our main contributions of the proposed algorithm include the joint denoising strategy without iteration, the self-similarity based image patch clustering and parallel analysis based adaptive principal component analysis for the low-rank approximation. Experimental results show that the proposed algorithm achieves highly competitive performance with the best state-of-the-art methods from subjective and objective measures of image quality, and can outperform them in most cases.

The rest of this paper is organized as follows. In Section 2, the proposed APCAS algorithm for image denoising is described. Section 3 shows the simulation and experimental results of the developed algorithm, and the comparison to the state-of-the-art methods. Finally, the discussions and conclusions are drawn in Section 4.

2. Proposed denoising algorithm

2.1. Method preview

In real-world digital-imaging devices, the acquired images are often contaminated by device-specific noise. Due to the existence of random noise in the acquisition process, magnetic resonance (MR) images are generally the most noisy. In the MR literatures [20,32], the noise in MR images is assumed to be Rician distributed with uniform or non-uniform variance across the image. However, Most of denoising methods in the literatures [9,54,10] have been developed assuming a Gaussian noise distribution with a spatially independent variance. In fact, the Gaussian assumption could be valid on MR images when SNR is larger than two [20]. For simplicity, the additive Gaussian noise model is adopted to simulate the noisy MR images for validation and evaluation of the denoising methods. As in the previous literatures [9,54,10], a simple noise model of independent additive type is generally used to describe the noisy image for simulation in the following formula:

$$y(x) = s(x) + \upsilon(x) \tag{1}$$

where x is a two-dimensional spatial coordinate; y is the observed image, s is the ideal noise-free image, and υ represents additive white Gaussian noise (AWGN) with zero mean and standard deviation σ_n.

Besides giving an image an undesirable appearance, the noise can cover and reduce the visibility of certain features within the image, which weakens the clinical diagnostic accuracy. Thus, it is necessary to remove the noise from MR images. Because of its advantage of not increasing the acquisition time and motion artifacts, postprocessing filtering techniques have been traditionally and extensively used in MR image denoising. In brief, the overview of procedures of our proposed method is described as follows (See Fig. 1):

1 Image pacth clustering. For each target patch, its corresponding patch group is formed by finding similar patches in the observed noisy image.
2 Signal dimension estimation. Parallel analysis is used to estimate the signal dimension of each similar patch group.
3 SVD-based low-rank approximation. The denoised image is obtained with the weighted averaging of the aggregate filtered patches that are constructed with the low-rank approximation.