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Image denoising with multidirectional shrinkage in directionlet domain

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A B S T R A C T

The efficient representation of edges is key to improving the image denoising performance. This motivates us to capture the edges and represent them with a sparse description. A novel image denoising method is proposed by exploiting the sparse representation of the edges and the multidirectional shrinkage. The enhancement of the sparsity is achieved by applying directionlet transforms constructed with the directions of the edges. Because the constructed directionlet transforms are performed along different directions, for each pixel we obtain many different estimates, one of which is optimal. The final denoised output is obtained by a weighted averaging of all individual estimates. Experimental results show that our method, compared with other multidirectional wavelet-based denoising algorithms, can effectively remove noise and preserve detail information such as edges and textures while avoiding the border effect.

1. Introduction

Denoising is a fundamental and widely studied problem in the field of image processing [1–3]. The main goal of an image denoising algorithm is to reduce noise while retaining image details such as edges and textures. Over the last few decades, many diverse tools have been explored to address this problem, from spatial filters to transform-domain methods such as wavelets.

Traditional spatial denoising methods based on the Perona–Malik(PM) model [4] or bilateral filtering [5] tend to exhibit a staircase effect. Since Buades et al. [4] presented the nonlocal means (NLM) method in 2005, the block similarity has been widely adopted for image denoising, and many adaptations of NLM have been proposed [7–15]. Among these different adaptations, the most significant extension is the optimal spatial adaptation method (OSA) [7], which introduces spatial adaptivity by jointly using block-based weights and variable window sizes, and achieves results competitive with previously published denoising methods of the time. Recently, block-based overcomplete representation methods [16–22] have shown satisfactory performance. Typical examples of such image denoising methods include the optimal weighted averaging algorithm [16], BM3D [17], and K-SVD [22]. For these methods, the key point is to obtain a good representation for each block of the image by using orthogonal transforms. Owing to block similarity and sparse representation, the image denoising method by sparse 3D transform-domain collaborative filtering (BM3D) achieves a state-of-the-art denoising performance, which is considered to be a benchmark representative. However, since the BM3D method uses blocks with a fixed square shape and a fixed scale over the entire image, the performance of this method is limited when dealing with edges, especially for edges with strong contrast.

Transform-domain-based denoising methods assume that the image can be well approximated by using a few large transform coefficients. That is, the image can be sparsely represented in the transform domain. Indeed, in

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the transform domain, most of the image information is concentrated in the few largest transform coefficients, while the noise is uniformly spread the low magnitude transform coefficients. Therefore, the most straightforward method of image denoising in the transform domain is to shrink the transform coefficients. The shrinkage strategy was pioneered by Donoho and Johnstone [23], who provided the expression of the universal threshold $\sqrt{2\sigma^2 \log^N}$ and reduced the noise by setting all wavelet coefficients smaller than the threshold value to zero. After the influential work of Donoho and Johnstone, many alternative methods have come forth [24–26]. A perfect example of these methods is the BLS-GSM algorithm [24], which achieves a good result by using a Bayesian estimator and establishing a Gaussian scale mixture model in the wavelet domain. For transform-domain-based denoising methods, owing to there being insufficient number of coefficients for the reconstruction of image information, it is easy to generate the pseudo-Gibbs or ringing artifacts.

Since the human visual system is more sensitive to edges and textures, directional wavelets or geometric wavelets for image denoising have become a hot topic in last several years. Compared with wavelet, multidirectional wavelets (for example, curvelet [27], contourlet [28], bandelet [29], or directionlet [30]) can provide a good sparsity for spatially localized details such as edges and textures. Thus, multidirectional-wavelet-based denoising methods [31–38] can produce better visual quality for highly structured image patterns.

In this paper, we propose a directionlet-transform-based image denoising method with multidirectional shrinkage. In order to provide efficient sparse representation for spatially localized details of an image, we take advantage of the multidirectionality of the directionlet transform. First, the noisy image is divided into two regions; second, the slope value of the dominant direction of each pixel belonging to the edge region is computed by linear least squares (LLS) method. Then, the directionlet transforms constructed with these slope values are applied to the entire image. Owing to the transform direction well adapted to the local direction, the image details can be effectively represented. Because the constructed directionlet transforms are performed along different directions, we obtain many different estimates of each pixel, one of which is optimal. The final denoised output is achieved by a weighted averaging procedure where we assign the maximum weight to the optimal approximation and less weight to the bad approximation. Fig. 1 shows the flow chart of the proposed method for image denoising.

Compared with previous works based on wavelets, our method has the following extensions. (i) We capture the geometrical features in images along two arbitrary directions instead of the predetermined standard and diagonal directions, (ii) we exploit the multi-directionality of the directionlet to improve denoising performance while eliminating the border effect, and (iii) we introduce an approach to obtaining the slope values of the local directions of edges.

The rest of this paper is organized as follows. After reviewing relevant work in Section 2, we introduce multidirectional shrinkage based image denoising method in Section 3. Section 4 shows and discusses the experimental results on five images. Finally, we conclude the paper in Section 5.

2. Related work

Since our method is also a multidirectional-wavelet-based denoising method, we briefly review previous work on multidirectional-wavelet-based image denoising methods in this section.

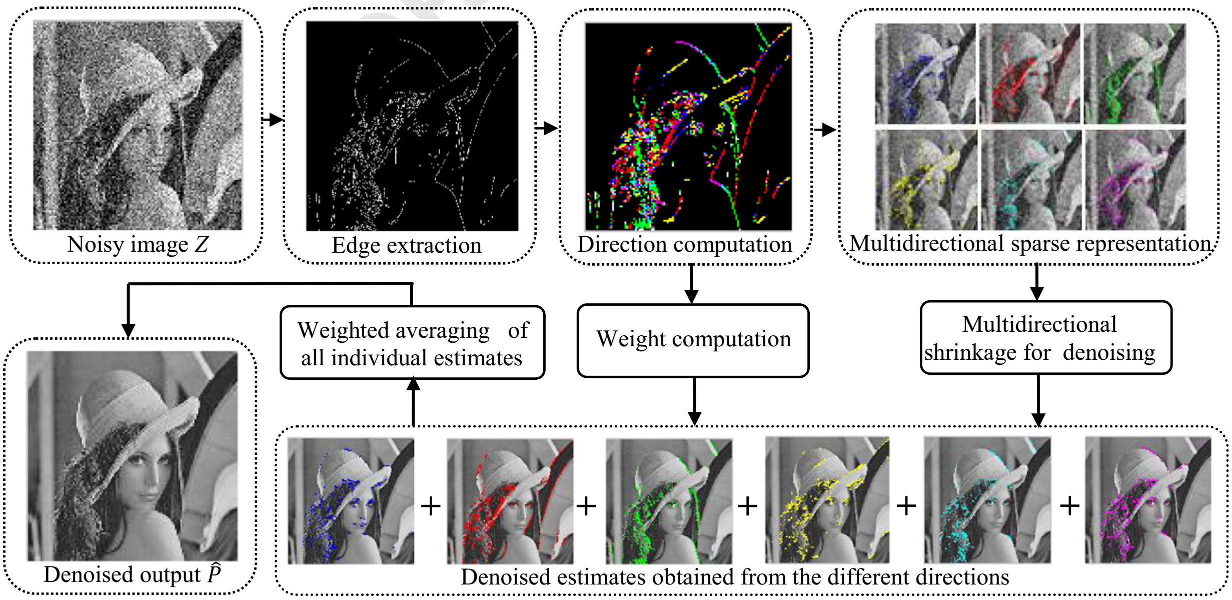

Fig. 1. The flow chart of the proposed method for image denoising, where each subimage is obtained by the directionlet transform with the direction of the pixels marked in the colour.

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