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Image denoising using local Wiener filter and its method noise

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ABSTRACT

This paper proposed a new image denoising method on local Wiener filter. Firstly, non-subsampled shearlet transform (NSST) is used to decompose noisy image since NSST is an effective multi-scale and multi-direction analysis tool in image processing. And then the high frequency NSST coefficients are denoised by a shrinkage function based on local Wiener filter. In this new shrinkage function, the method noise of local Wiener filter is employed effectively by using the Stein's unbiased risk estimate and linear expansion of thresholds (SURE-LET) strategy. Finally, the inverse NSST is used to obtain the denoised image. Experimental results show that the proposed method is very good in performance compared to the state-of-the-art wavelet-based algorithms.

1. Introduction

During acquisition and transmission, images are often corrupted by noise. Denoising is therefore the basic problem in image processing application. The purpose of denoising is then to reduce noise level, while preserving the image features such as edges and textures and so on as accurately as possible. Many image denoising methods have been proposed in the literature. Among these methods, Wiener filter has received an increasing attention because of its simplicity and effectiveness. Up to now, a vast literature has emerged on image denoising based on Wiener filter.

In Refs. [1,2], the wavelet coefficients are assumed to be conditionally independent zero-mean Gaussian random variables with high local correlation. The wavelet coefficients variances are estimated by using an approximate maximum a posteriori probability rule. And then the local Wiener filter is used to restore the noisy wavelet image coefficients. This method is very simple but produces very good results. For this method, the estimate of wavelet coefficient variance is very important for denoising performance. In Ref. [3], the preprocessing with a thresholding operation is used to improve these estimates. In Ref. [4], the final estimate of wavelet coefficient variance is computed by using the weighted average of the multiple estimates obtained from differently shaped windows. In Ref. [5], the directional window is used to improve the performance of local Wiener filter.

Although the above mentioned Wiener filter methods achieved good results, the performance is limited since these methods operated in wavelet domain. This is because that traditional two-dimensional wavelet transform can not perform as well with multi-dimensional data such as images which are usually governed by anisotropic features such as edges. So, some new algorithms on Wiener filter were put forward. They are based on new multi-scale analysis tools such as dual-tree complex wavelet transform (DT-CWT) [6] and shearlet [7] and etc. For example, the SURE-NeighShrink employing the dual-tree complex wavelet transform (DT-CWT) was designed in Ref. [8]. In this method, the Stein's unbiased risk

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Noisy image → Nonsubsampled shearlet transform → Transform high frequency coefficients by using Wiener filter and its method noise → Inverse nonsubsampled shearlet transform → Denoised image

Fig. 1. Proposed denoising method.

estimate (SURE) of the mean squared error (MSE) is used to determine optimal threshold and neighboring window size of NeighShrink method by using neighbour dependency and customized wavelet and threshold proposed in Ref. [9]. The related experiments demonstrate the SURE-NeighShrink method on the DT-CWT achieves better results than that on the decimated wavelet transform. Here one calls NeighShrink a Wiener filter method since it is equivalent to Wiener filter in essence and can be turned into Wiener filter in form. In Ref. [10], Zhang et al. proposed multiple-step local Wiener filter (MSLWF) image denoising algorithm based on DT-CWT. This method is simple and efficient. The whole algorithm can be considered as a discretized implementation of adaptive heat diffusion equation. In Ref. [11], a new algorithm via wiener filter in the shearlet domain (Shear-Wiener) is proposed. The Wiener filter with the threshold operation in Ref. [3] is used shrink the noisy shearlet coefficients. The performance of this method relies on shearlets which are equipped with a rich mathematical structure and associated with a multi-resolution analysis and has the features of directionality, localization, anisotropy and multiscale. In addition, the patch-based Wiener filter is proposed in Ref. [12]. Although this method obtains the similar performance compared to the block- matching with 3D transform domain collaborative filtering (BM3D) proposed by Dabov et al. [13]. But, the patch-based Wiener filter method and BM3D method employing Wiener filter are a little complex in implementation, they are not feasible in practice. For this, the attention is focused on local Wiener filter in this paper. At the same time, an observation is found that the corresponding method noise is not considered in the design of algorithm for aforementioned Wiener filter methods. This paper will deal with this problem.

At this time, the SURE-LET method in Refs. [14,15] is noted. This method can integrate the different estimates of noise-free image effectively and produce the better results than each estimate. So, a new algorithm on Wiener filter is formed in this paper. This new method operates in nonsubsampled shearlet transform (NSST) domain because NSST is a fully shift-invariant, multi-scale, and multi-direction expansion. In the high frequency sub-bands, the Wiener filter and its method noise by using SURE-LET strategy is combined to remove the noise components of NSST coefficients. Unlike [8], the proposed method focuses on the determination of the weight of new threshold function based on Wiener filter. Also unlike [11], the proposed method employs the method noise in improving local Wiener filter. Also unlike the point-wise SURE-LET methods in Refs. [14,15], the proposed method uses local Wiener filter to form new shrinkage function.

The rest of this paper is organized as follows. Section 2 presents the proposed image denoising algorithm. Firstly, an overview of NSST is provided. Secondly, local Wiener filter is reviewed. Thirdly, the proposed thresholding function on local Wiener filter and its method noise is formed. Fourthly, the performances and parameters of algorithm are discussed and analyzed. Section 3 presents experimental results. Section 4 concludes the paper.

2. Proposed image denoising method

In this section, the denoising of an image corrupted by white Gaussian noise with zero mean and variance σ_n^2 will be considered. Since NSST is linear, in each subband the NSST coefficient of noisy image can be formulated as:

$$y(i,j) = x(i,j) + n(i,j) \tag{1}$$

where $y(i,j)$ is the noisy wavelet coefficient, $x(i,j)$ the true coefficient and $n(i,j)$the noise component with Gaussian distribution with zero mean. The variance of $n(i,j)$ can be computed by Monte-Carlo approach. The computed variance is represents as $\hat{\sigma}^2$. Suppose $x(i,j)$ satisfies conditionally independent zero-mean Gaussian distribution and the variances are independent and identically distributed and local strongly correlated random variables. So, as with [1,2], it is possible that restoring the clean wavelet coefficients by employing Wiener filter. The main stages of the proposed denoising method are illustrated in Fig. 1. In the following, the proposed algorithm is described in detail.

2.1. Nonsubsampled shearlet transform (NSST)

Shearlet is a nonisotropic version of the continuous wavelet transform with a superior directional sensitivity by taking advantage of the classical theory of affine systems [7]. In dimension $n = 2$, shearlet transform is defined as the mapping

$$SH_\psi f(u, v, t) = \langle f, \psi_{u,v,t} \rangle \tag{2}$$