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Two-step Image Denoising

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ABSTRACT

Image denoising is an area of active research. Many image denoising techniques have been proposed in literature both in spatial and transform domain. Image denoising always strikes a balance between noise removal and preserving edge information. An improved two-step approach using stationary wavelet transform is proposed in this paper. The first-step uses neighshrinksure followed by the nonlocal means method for denoising. The simulation results on synthetic and real images demonstrates the improvement of the proposed method.

Keywords:

Image denoising, Wavelet transform, Neighborhood dependency

1. INTRODUCTION

Denoising is considered as one of the major issues in image processing. The noise in an image can be due to camera sensors, atmospheric conditions or transmission through a medium. Denoising has its root in wide range of applications such as segmentation, recognition, classification etc. For example, in medical images, the presence of noise can lead to wrong diagnosis. With respect to the source of occurrence of noise various models such as Gaussian, exponential, Rayleigh, uniform and impulse are used in literature. In most of the applications additive white Gaussian noise (AWGN) is used [16]. Over past few decades, a variety of methods have been introduced to suppress the noise in digital images. These methods are primarily classified into two categories: spatial and transform domain methods.

1.1 Spatial domain denoising

In spatial domain methods, the denoising procedure is directly applied on pixels. The basic denoising methods uses the estimation of mean and variance locally and most cited among them is local Wiener filtering [19]. The estimated image is shown to be depending on local variance of noise and signal. This method is used for image and video denoising. It assumes that all the intensity values in the local region are similar. However, near edges the method fails to remove noise due to high value of local variance [18]. Bilateral filter [24] is a non-linear filter that makes use of local windows and can be used in both iterative and non-iterative methods. At any location (i, j) the pixel value is calculated by considering photometric and geometric similarities between neighboring pixels within spatial window. In order to make this method non-iterative, a large spatial window has to be considered and it makes the resultant smoother. In case of iterative process, the smoothness parameters need to be tuned to get better results [15]. Total variation (TV) minimization in discrete version [9] applied for denoising used graphs and edge derivatives to find edges. It is an iterative process. The regularity and fidelity terms need to be fine tuned to get good quality of edges with noise suppression [6]. Nonlocal means (NLM) is one of the most discussed and state-of-the-art denoising methods [4, 5, 6]. An image consists of repeated structures. NLM averages these similar structures to reduce the noise. At location i, the estimated value $NL[y](i)$ is given by weighted average of all pixels in the image. This method is computationally intensive [20]. For an image with M pixels, M weights have to be computed at each pixel.

1.2 Transform domain denoising

Denoising can be achieved using various transforms [17, 3, 2]. In this paper, the discussion is being limited to wavelet transform. In wavelet denoising, thresholding is popular due to its simplicity. Soft and hard thresholding [13], where each coefficient is compared against a threshold to achieve denoising. Soft thresholding (T_{soft}) is shrink or kill process; whereas hard thresholding (T_{hard}) is keep or kill process. At beginning, the threshold is applied only to detail coefficients. The algorithm offers an advantage of smoothness and adaptation. But the algorithm does not take care of edges and tend to retain artifacts. Translation invariant (TI) denoising [11] performs denoising over circularly shifted images and averages them to avoid artifacts. It is extended to TI multiwavelets [7] for better results. In wavelets, current coefficient will have an influence of its surrounding coefficients. In the paper [25], a thresholding scheme that uses immediate neighbor is proposed. The results revealed an improvement over term-by-term denoising. The idea is extended to multiwavelets by [8]. The idea of [25] is extended to neighshrinksure [12] to obtain better results. Neighshrink, neighsure and neighlevel [10] also uses neighbor coefficients for denoising. Bivariate shrinkage [23] uses child-parent concept with respect to various levels of wavelet decomposition. It considers that, if parent coefficient has noise, then the child coefficient will also have noise. In image denoising there is always a tradeoff between noise suppression and quality of reconstructed image. Hence most of the denoising methods tend to oversmooth details and/or retain noise/artifacts. In this paper, a two-step image denoising scheme that uses wavelet transform is presented. In the first-step of denoising, neighshrinksure [12] is used. It provides noise suppression but with artifacts. In second-step, nonlocal means [4, 5, 6] is applied to the output of first-step. When compared to individual methods, the step-by-step method provides better results.

2. METHOD OF DENOISING

The noise model under consideration is

$$y_s = x_s + \eta_s \tag{1}$$

where, x_s is clean image, y_s is noisy image, η_s is Gaussian noise and subscript s indicates spatial domain.
When the wavelet transform is applied, most of the information in the image/signal will be compressed into relatively few large valued coefficients that include major areas of spatial activity. Due to linearity of wavelet transform, the additive noise remains additive in transform domain too [22]

$$Y = X + N \tag{2}$$

where, Y, X are wavelet transformed noisy and noise-free coefficients respectively and N is Gaussian noise. If the noise variance is known, it can be directly used in denoising process to

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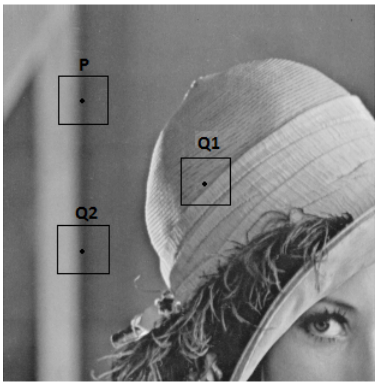


Fig. 1. Example of self-similarity in image.

derive better results. But it is not true for all cases. Hence the estimation of noise variance can be done using median estimator applied to HH subband of wavelet transformed image [14],

$$\hat{\sigma} = median\left(\frac{|w_{HH}|}{0.6745}\right) \tag{3}$$

Wavelet transform is a valuable tool in signal and image processing [21]. Here, the stationary wavelet transform (SWT) is being used. Literature indicates [22] that SWT consumes more memory by having redundant coefficients in transformed image. This redundancy is advantage in many imaging applications and the same is being used for denoising in this paper. For transformed image, two-step denoising process is applied. In the first-step, smoothing is achieved by using optimized thresholding [12]. It uses different threshold for different subband. The threshold is determined by considering neighborhood in each subband that uses following procedure;

$$SURE(w_s, \lambda, L) = N_s + \sum_n ||g_n(w_n)||^2 + 2\sum_n \frac{\partial g_n}{\partial w_n} \tag{4}$$

where N_s is number of coefficients w_n in w_s

$$||g_n(w_n||^2 = \begin{cases} \frac{\lambda^4}{S_n^4} w_n^2 & (\lambda < S_n) \\ w_n^2 & \text{otherwise} \end{cases} \tag{5}$$

$$\frac{\partial g_n}{\partial w_n} = \begin{cases} \lambda^2 \ \frac{S_n^2 - 2w_n 2}{S_n^2} & (\lambda < S_n) \\ -1 & \text{otherwise} \end{cases} \tag{6}$$

The threshold λ^s and neighbor window size L^s for the subband s is;

$$(\lambda^s, L^s) = arg \min_{(\lambda, L)} SURE(w_s, \lambda, L) \tag{7}$$

For details refer [12]. Applying neighshrinksure on noisy image, noise is suppressed to a greater extent; but retains artifacts. The second-step of denoising involves the use of nonlocal means (NLM) [4, 5, 6] to the output of first-step. NLM assumes that, an image contains self-similar structures and averaging them reduces noise. Figure 1 shows the similarity concept. Three neighbors P, $Q1$ and $Q2$ are considered. P and $Q2$ are similar, where as P and $Q1$ are not similar. The self similarity concept can be used to reduce the noise in an image. NLM denoised image is computed using;

$$NL[y](P) = \sum_{J \in I} w(p, q) y(q) \tag{8}$$

where, $w(p, q)$ is the weight meeting the condition $0 \leq w(p, q) \leq 1$ and $\sum_q w(p, q) = 1$; y is noisy representation.

This weight function is given by;

$$w(p, q) = \frac{1}{z(p)} e^{||y(N_1) - y(N_2)||^2_{2,F}/h^2} \tag{9}$$

$z(p)$ is a normalized constant defined as;

$$z(p) = \sum_q e^{||y(N_1) - y(N_2)||^2_{2,F}/h^2} \tag{10}$$

where, h is the parameter to control smoothness of resultant image. Higher the h leads to oversmoothness; lower the h retains noise.
After applying NLM to each subband; inverse wavelet transform is applied to get final reconstructed image in spatial domain.

3. RESULTS AND DISCUSSION

In this section, a comparison between proposed method and other denoising methods is presented. For quantitative analysis PSNR is used as benchmark;

$$PSNR = 10log_{10}\left(\frac{255^2}{MSE}\right) \tag{11}$$

where, MSE is mean square error.
The similarity measure is given by using Structural similarity index (SSIM) [26]. It is the function of luminance $l(\cdot)$, contrast $c(\cdot)$ and structure $s(\cdot)$. It is given by;

$$SSIM(x, \hat{x}) = f(l(x, \hat{x}), c(x, \hat{x}), s(x, \hat{x})) \tag{12}$$

where, x and $\hat{x}$ are noise-free and reconstructed images respectively. In practice, usually single value of quality measure is used for entire image. Hence mean SSIM (MSSIM) index is used to evaluate overall image quality and is given by;

$$MSSIM(x, \hat{x}) = \frac{1}{M} \sum_{j=1}^{M} (x_j, \hat{x}_j) \tag{13}$$

where, x_j and $\hat{x}_j$ are the image contents at j^{th} local window; M is the number of local windows of the image. Lena (512×512), Barbara (512×512) and Boat (512×512) images are considered for simulation. Noisy images are generated by adding additive Gaussian noise of different variance values. Denoising is achieved by wavelet based methods such as soft thresholding [13], cycle-spinning [11], Neighshrinksure [12], Multispinning [1] and the proposed method.
For result, only a part of Lena image is shown, whereas the simulation is conducted on complete image. Lena image degraded by additive noise of variance 20 is considered (Figure 2(a)). First the image is denoised by soft thresholding. It suppresses noise by smoothing. Along with noise, edges are also smoothed and create artifacts near edges (Figure 2(b)). Cycle-spinning also uses soft thresholding, but on cyclically shifted versions of noisy images. This method avoids artifacts that are created in soft thresholding by averaging the reconstructed images and is shown in Figure 2(c). Neighshrinksure uses different threshold value for different subbands. The threshold is derived by considering the neighborhood pixels (usually 3×3 or 5×5) in a subband and determines an optimal threshold for that subband. As the noise in image increases, this method creates artifacts (Figure 2(d)). To solve this, multispinning neighshrinksure is introduced. It uses randomly shifted images. On each of these images, neighshrinksure is applied. This avoids the artifacts of previous method and provides good quality edge reconstruction. Due to random shifts, this method creates slightly blurring effect on reconstructed images (Figure 2(e)). To overcome all these problems, stationary wavelet transform and a two-step denoising process is used. In

Fig. 2. Denoising of Lena image using various wavelet based methods. (a) Image with noise variance 20. (b) Soft thresholding (c) Cycle-spinning (d) Neighshrinksure (e) Multispinning (f) Proposed method.

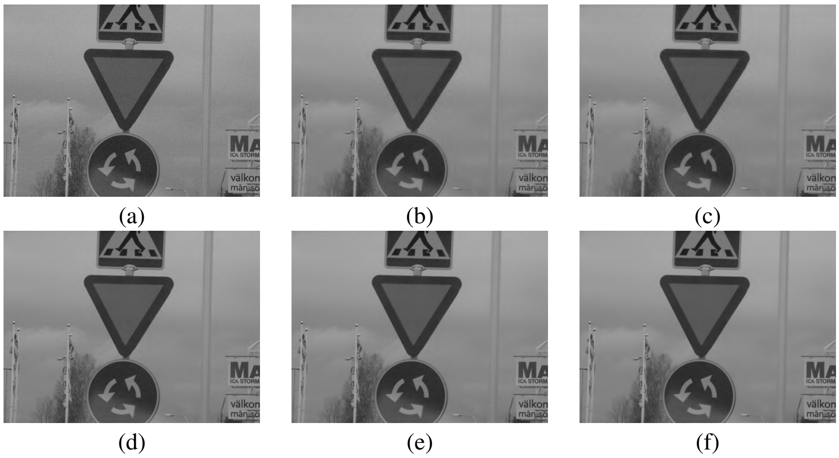


Fig. 3. Denoising of real traffic signal image using various wavelet based methods. (a) Image with unknown amount of noise. (b) Soft thresholding (c) Cycle-spinning (d) Neighshrinksure (e) Multispinning (f) Proposed method.

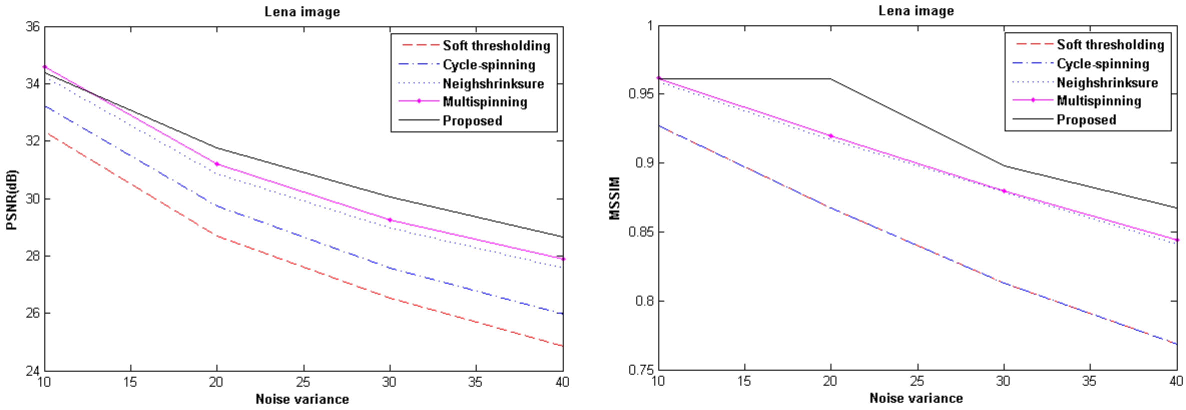
Table 1. Quantitative analysis using PSNR (dB)

σ	Soft Thresholding	Cycle-spinning	Neighshrinksure	Multispinning	Proposed method
Lena (512×512)					
10	32.3150	33.2535	34.2472	34.6043	34.3975
20	28.7052	29.7462	30.8608	31.1886	31.7598
30	26.5465	27.5761	28.9554	29.2425	30.0600
40	24.8584	25.9683	27.5880	27.8755	28.6475
Barbara (512×512)					
10	29.9923	30.8175	32.6344	32.8938	33.3422
20	26.2656	27.0263	28.6142	28.9220	29.0048
30	24.2154	25.0307	26.4020	26.7864	26.8362
40	22.8747	23.7205	25.0428	25.4011	25.3016
Boat (512×512)					
10	30.7081	31.5439	32.6133	32.8561	32.9473
20	27.3385	28.1711	29.0937	29.3193	29.4225
30	25.3045	26.2126	27.1258	27.3892	27.8590
40	23.8757	24.8039	25.8851	26.0895	26.5906

the first-step neighshrinksure is used to reduce noise. It is continues to second-step denoising by applying NLM. The reconstructed image will be free from artifacts and has good reconstruction quality (Figure 2(f)). Further, the simulation is carried-out on Barbara and Boat images and better results are obtained.

Table 2. Mean structural similarity index (MSSIM)

σ	Soft Thresholding	Cycle-spinning	Neighshrinksure	Multispinning	Proposed method
Lena (512×512)					
10	0.9274	0.9274	0.9592	0.9615	0.9609
20	0.8675	0.8675	0.9171	0.9198	0.9312
30	0.8129	0.8129	0.8792	0.8797	0.8979
40	0.7683	0.7683	0.8412	0.8438	0.8671
Barbara (512×512)					
10	0.9173	0.9173	0.9649	0.9659	0.9694
20	0.8334	0.8334	0.9179	0.9170	0.9236
30	0.7672	0.7672	0.8737	0.8680	0.8780
40	0.7156	0.7156	0.8339	0.8250	0.8326
Boat (512×512)					
10	0.9072	0.9072	0.9556	0.9571	0.9593
20	0.8240	0.8240	0.8975	0.9009	0.9039
30	0.7602	0.7602	0.8462	0.8501	0.8636
40	0.7039	0.7039	0.7991	0.7986	0.8198



(a) (b)

Fig. 4. Graph showing PSNR and MSSIM values of various denoising methods for Lena image. (a) PSNR vs Noise variance (b) MSSIM vs Noise variance.

Finally, the algorithm is also tested on real images *(Traffic signal image is the courtesy of Dr. Hasan Fleyeh, Dalarna university, Sweden)*. Figure 3 shows the results. It indicates that, the text part and constant gray level values in signal region are much better represented in the output of proposed method.

Table 1 and Table 2 shows the quantitative analysis (PSNR) and mean structural similarity index (MSSIM) [26] respectively. It can be observed that, except for one case in all remaining the PSNR and MSSIM is highest in proposed method. Figure 4 shows the graphical representation of obtained PSNR and MSSIM for Lena image as an outcome of various denoising approaches. It also magnifies that the proposed method is better than other methods.

4. CONCLUSION AND FUTURE DEVELOPMENTS

In this paper, two stage denoising method for suppressing Gaussian noise is presented. The results are compared with other wavelet denoising methods. The results indicate the improvement of the proposed method over the existing approaches in terms of visual quality. For quantitative analysis, PSNR and MSSIM are used. Results indicate that the proposed method provides better results by suppressing noise and preserving edges.

This paper assumes usual additive Gaussian noise model. However, this assumption may not be always valid. For example, medical images such as ultrasound image usually suffer from speckle noise. It is interesting to explore methods for denoising in such cases.

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