An Effective Noise Estimator for Use in Noise Reduction

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***Abstract*— Conventional noise reduction filtering schemes realize limited improvements of the peak signal-to-noise ratio (PSNR) in the low-level noisy images. The flatness degree and the edge information are effectively used to estimate the noise volume. We propose a noise estimator for reducing noise in the AWGN (additive white gaussian noise) corrupted images using three intermediate image maps (FGM(flatness gray map), FIM(flatness index map), NEM(noise estimate map)). The proposed noise estimator is fed into the conventional noise reduction filters as a pre-processor. The performance of noise reduction is tested in the various AWGN corrupted images.**

Index Terms— noise reduction, noise estimation, low-level noise filtering

I. INTRODUCTION

Noise reduction in digital image applications has been a longstanding problem. Noise is introduced into digital imaging devices when the visual surrounding information is captured through image acquisition devices including optical lens, color filter arrays, photo sensors, etc. The primal cause is the lack of the dynamic range and sensitivity against the variant brightness. The problem affects the performance of image process, image storage, and image communication. Many researches have been reported to improve the image quality demanded from user expectations using diverse noise reduction schemes. AWGN corrupts digital video signals during their transmission through communication channels. For the noise reduction, several linear filtering approaches have been applied to the noise reduction [1].

Linear filters such as a mean filter and a Gaussian filter are amenable to analysis in the Fourier domain and require low complexity [2]. However, the blurring effect of the edge component occurs since the local brightness information is not accessible. In addition, such nonlinear filters including a median filter, a k-nearest neighbor (NN) algorithm, symmetric NN algorithms, and a sigma filter have been reported to improve the blurring effect by means of adjusting individual pixels from the estimate of relations of pixels similarity and pixels adjacency. The design of nonlinear filters requires more sophisticated algorithms than that of linear filters. On the other hand, the nonlinear filters successfully reduce the noise while preserving the original image. In particular, Bilateral filter, SUSAN filter, and Non-Local (NL) means filter are reported useful to preserve the edge information [2]-[3]. Bilateral and SUSAN filters use the domain and range kernel for the spatial and intensity region respectively. NL-means filter pay the high computational cost for the pixel-by-pixel window matching. Other iterative adaptive smoothing and anisotropic diffusion noise reduction techniques have been applied into a “cartoon” [2].

These filtering approaches have shown the limited performance for practical applications because of the assumption that the Gaussian noise distribution or noise level is known. Given unknown noise characteristic, noise estimate has the challenges in terms of the accuracy and the computational complexity. In [4]-[5], the noise is estimated by computing the difference between the noisy image and the low-pass filtered image. The results show better performance when compared with each of the adaptive Gaussian filters and the estimate of the standard variance of the individual block. In [6], Shin et. al. proposed a block-based noise estimate that makes use of the adaptive Gaussian filter combined with the blocks classification based on the standard deviation of their intensities. This method is reported the best performance among the Lee and Hoppel[7], Olsen[8], Rank et al.[9] methods. However, the performance of the noise estimate can be varied according to the block size. Given the noisy image containing much more information of the edge component, the noise volume can be incorrectly increased. For example of a noise reduction, we used seven popular linear and nonlinear filters of an average filter, a k-NN algorithm, a symmetric NN algorithm, a global sigma filter, a local sigma filter, a Gaussian filter, and a median filter. We added the various AWGNs to a “Lenna” image. Seven different conventional filters were employed to compare the PSNRs between the original image and the corrupted input images, as shown in Figure 1. The linear filters and the nonlinear filters showed the higher PSNRs than that of the input image around at the 6 standard deviation above. However, around at the 6 standard deviation below, the

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PSNRs of the filtered images are lower than that of the input image. This implies that the AWGN is globally embedded in the image. If the local noise characteristic can be estimated in the image, more accurate noise estimate can be used to improve the performance of the above seven filters.

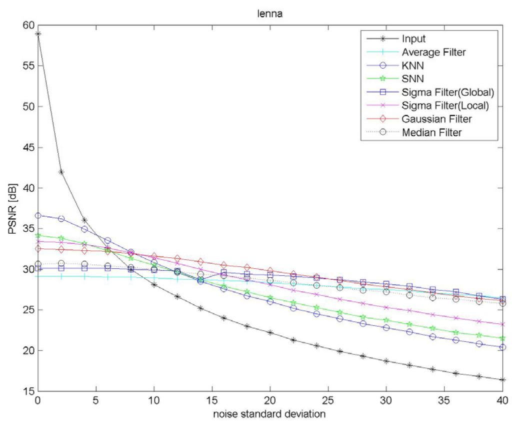


Fig. 1 Performance comparisons of conventional noise-reduction techniques for the low-level noise image in the "Lenna" image.

In order to increase the low-level noise reduction performance of the conventional filters, we propose a noise estimate which makes use of the local noise characteristic and use three intermediate image maps (FGM, FIM, NEM). The flatness degree and the edge information are efficiently used to estimate the low-level AWGN volume. Combining with the conventional noise reduction filters, the proposed noise estimator benefits from the low-level noise reduction as a preprocessor.

II. PROPOSED NOISE ESTIMATOR

The proposed noise estimator consists of three stages. In the first stage, we prepare the flatness gray map (FGM) image. Given the noisy image $x(m,n)$, the FGM image is calculated by

$$FGM_i = \frac{1}{L-1}\sum_{m,n}\left|x^i(m,n) - x_c^i(m,n)\right| \quad (1)$$
$$m \in [1, M],\ n \in [1, N]$$

where L is the mask size, M is the width, N is the height, $x_c^i(m,n)$ is the central pixel, $x^i(m,n)$ is the neighboring pixel in the ith mask window. The FGM image provides the flatness degree and the edge information from the underlying image.

In the second stage, the histogram of the pixel bright values ranging from 0 to 255 is calculated to obtain its cumulative distribution function (CDF) $f(FGM_i)$. To deal with the dynamic variance of the AWGN volume and image quality, we empirically chose the 80% threshold as optimum. Figure 3 shows the results of the validating threshold selection ranging from 0 to 100% with 4 different images. Although the number of the testing images is limited, For about 10 standard deviation of AWGN noise estimate, the 80% threshold resulted in the best. The 80% is the threshold to separate the image pixels into the flat region and the non-flat region as shown in Eq. (2).

$$\delta^i(m,n) = \begin{cases} 1, & if\ \ f(FGM_i) \geq 0.8 \\ 0, & otherwise \end{cases} \quad (2)$$

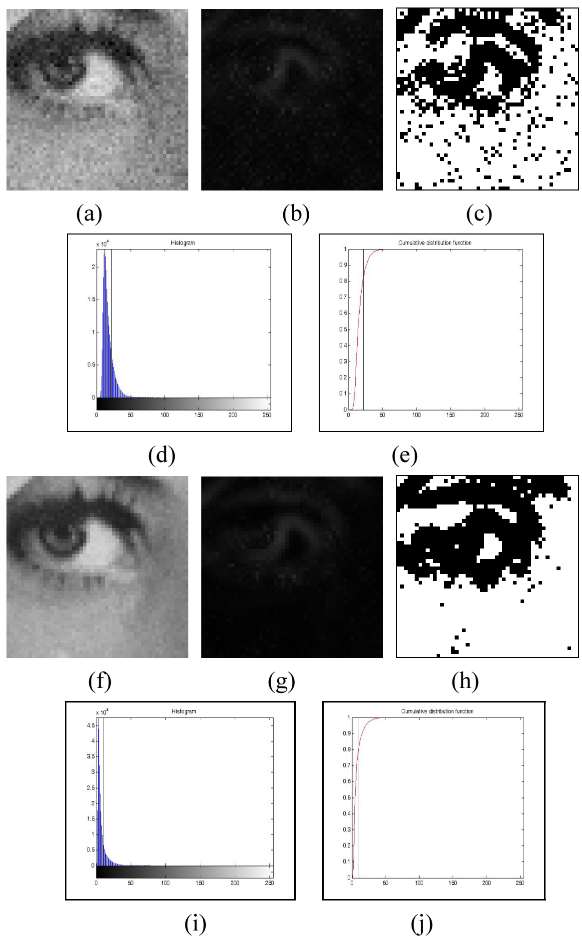


Fig. 2 Upper images with PSNR=26dB: (a) input noisy image, (b) the FGM image, (c) the FIM image, (d) the histogram of the FGM, and (e) the CDF of the FGM. Lower images with PSNR=38dB: (f) input noisy image, (g) the FGM image, (h) the FIM image, (i) the histogram of the FGM, and (j) the CDF of the FGM.

The flat region includes the edge information as well as the noise information. We denote the $\delta^i(m,n)$ image by the flatness index map (FIM). Figure 2(a) and (f) show left eyes of the “Lenna” image corrupted by the different volume with PSNRs (26dB and 38dB, respectively), Figure 2(b) and (g) show the FGMs, and Figure 2 (c) and (h) show the FIMs. Figures 2(d) and (i) show the histogram of the FGMs, and Figure 2(e) and (j) show the cumulative distribution functions of the FGMs. The vertical line indicates the 80% threshold.

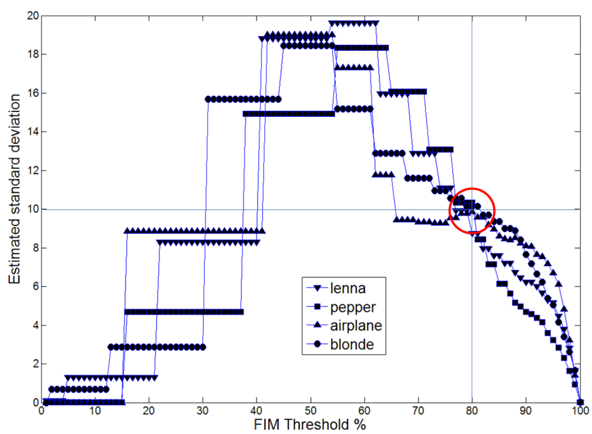


Fig. 3 Performance comparison according to the FIM threshold %

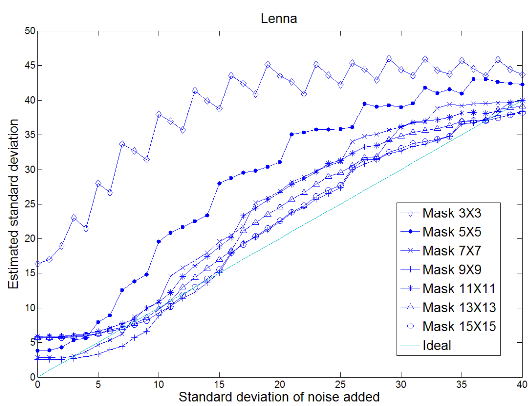


Fig. 4 Performance comparison according to the various mask size.

All images size used in this letter are 512x512 size. Every mask based image processing methods take effect by the mask size in the processing. In this letter, we can apply with the various mask size only in the FGM image generation processing step. Figure 4 shows the estimation performance according to the various mask size. Because of the central pixel represents the flatness degree in that area. To large the mask size, to better performance up to 9x9 size, But too large mask is rather harmful for the performance. So it is required that the processing with the optimal mask size and normalizing the input image size to the 512x512 size. The 9x9 mask size performed the best in the “Lenna” image.

In the third stage, we estimate the noise volume threshold $\delta^i(m,n)$ in the FIM. If the number of $\delta^i(m,n)$ is less than 3 and $x^i(m,n)$ = 0, $\delta^i(m,n)$ is assumed as the noise pixel. The noise estimate map (NEM) is calculated by Eq.(3) and is for removing the edge components in the FIM image and generating the NEM image which only contain the noise component. Noise pixel composed of the small pixels and pixel threshold factor (pixel_th) is the empirical value. The reason using the static 3x3 mask size in Eq.(3) is for counting the small pixel and 3x3 mask size is the minimum size including the central pixel. Figure 5 shows the optimal estimation results in the 3 pixel for the noise standard deviation 10 gaussian added noise. So we select the pixel threshold with 3.

$$NEM(m,n) = \begin{cases} 1, & if \ \sum_{m=}\sum \delta^i(m,n) \le pixel\_th \\ & \quad and \ if \ x^i(m,n) = 0 \\ 0, & \quad otherwise \end{cases} \tag{3}$$

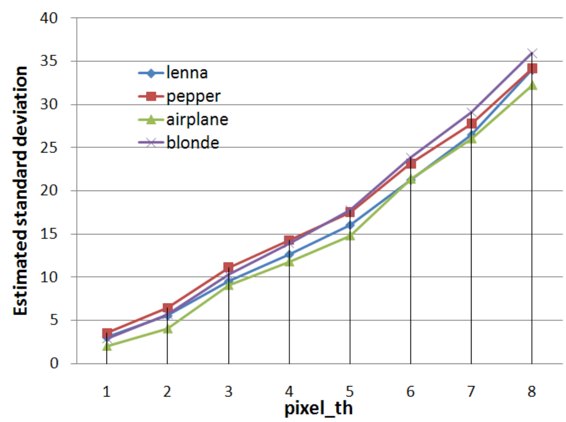


Fig. 5 Performance comparison of the noise estimator for the different mask sizes and noise volume.

$$NV = \alpha \times \frac{\sum_{m,n} NEM(m,n)}{M \times N} \times 100 \tag{4}$$

where α is the conversion factor of standard deviation for the noise volume. We empirically choose α as 2.47 as optimum.

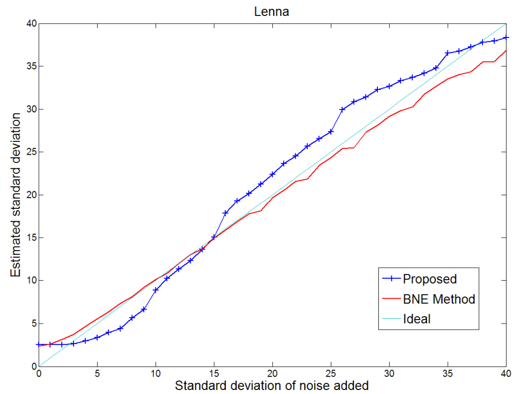
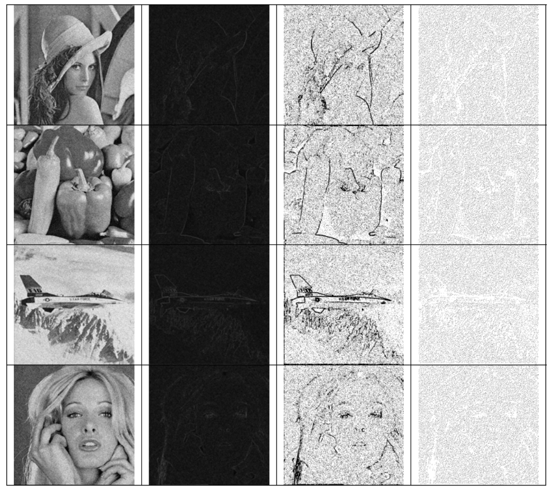


Fig. 6 Performance comparison with the BNE and proposed method.

As typical noise estimator, there is the standardized median of absolute deviation from the median (MAD [10]). But MAD approach is base on the wavelet and assumes that the coefficients of the finest decomposition level are associated only to the noise and uses the median of absolute value of these coefficients for variance estimation [11]. Instead of comparison with MAD, we compare with the block-based noise estimation method proposed by Shin et al. which is very similar approach to this method. Figure 6 shows the performance comparison with the BNE.

Figure 7 depicts simulation results in the standard deviations 10 and 30 of additive noise volume respectively for the four test images. Figure 7(a)(e) is input noisy images. Figures 7(b)(f) and (c)(g) are the corresponding the FGMs and the FIMs, respectively. Figure 7(d)(h) is the resulting NEMs. From the figures, we can see that the flatness degree decreases in the FGMs and FIMs as the standard deviation increases. The edge information is removed by using Eq. (3) and the estimated noise volume remains increasingly in the NEMs.

(a) (b) (c) (d)



(e) (f) (g) (h)

Fig. 7 Simulation results in the standard deviations 10 and 30 of the additive noise volume: (a)(e) input noisy image, (b)(f) the FGMs, (c)(g) the FIMs, and (d)(h) the NEMs.

III. RESULTS AND DISCUSSION

The noise reduction filtering was simulated using the proposed noise estimator in the “Lenna” image. We made use of the seven conventional filters as shown in Figure 1. The standard deviations range from 0 to 40. Figure 8 shows the improved performance of the noise reduction. The proposed noise estimator fed into the conventional filters significantly improved the PSNRs around at the 8 standard deviation or smaller. Around at the 8 standard deviation or higher, the performance of the noise reduction filtering is identical with that as shown in Figure 1. The proposed noise estimator measures effectively the additive noise volume and, thereby, reduces the low-level noise.

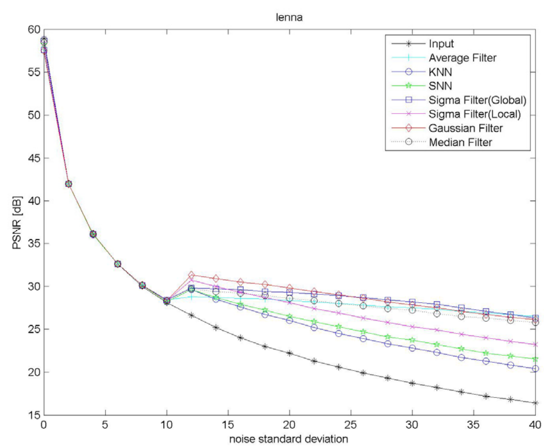


Fig. 8 Improved performance of conventional noise-reduction techniques for the low-level noise image with the proposed method.

V. CONCLUSIONS

In the paper, we proposed the noise estimator for filtering based noise reduction. The proposed flatness information and its consecutive binary mapping utilization were capable of removing the edge information and estimating the noise volume in the various noisy images. The 9x9 mask size performed the best to estimate the additive noise volume. The simulation results show that when the conventional noise reduction filtering techniques combined with the proposed noise estimator significantly improved the PSNRs in the low-level noisy images as well as in the high-level noisy images.

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REFERENCES

[1] R. C. Gonzalez, R. E. Woods and S. L. Eddins, “Digital Image Processing using MATLAB,” *Pearson Prentice Hall*, pp. 89-107, 2004."

[2] A. Buades, B. Coll, and J.M. Morel, “A non local algorithm for image denoising,” *IEEE Computer Vision and Pattern Recognition* 2005, Vol. 2, pp. 60-65, 2005.

[3] S.M. Smith and J.M. Brady, “SUSAN-A New Approach to Low Level Image Processing,” *International Journal of Computer Vision*, Vol. 23, No. 1, pp. 45-78, May 1997.

[4] R.C. Bilcu and M. Vehvilainen, “A New Method for Noise Estimation in Images,” *Proc. IEEE EURASIP International Workshop on Nonlinear Signal and Image Processing*, Sapporo, Japan, May 2005.

[5] S.C. Tai and S.M. Yang, “A Fast Method for Image Noise Estimation Using Laplacian Operator and Adaptive Edge Detection,” *ISCCSP* 2008, Malta, March 2008.

[6] D.-H. Shin, R.-H Park, S. Yang, and J.-H. Jung, “Block-Based Noise Estimation Using Adaptive Gaussian Filtering,” *IEEE Trans. on Consumer Electronics*, Vol. 51, No. 1, pp. 218-226, 2005.

[7] J.S. Lee and K. Hoppel, “Noise modeling and estimation of remotely-sensed image,” in *Proc. Int. Geoscience and Remote Sensing*, Vancouver, Canada,, Vol. 2, pp. 1005-1008, June 1989.

[8] S. I. Olsen, “Estimation of noise in images: An evaluation,” *Graphical Models and Image Process.*, Vol. 55, pp. 319-329, July 1993.

[9] K. Rank, M. Lendl, and R. Unbehauen, “Estimation of image noise variance,” *IEE Proc. Vis. Image Signal Processing*, Vol. 146, pp. 80-84, Apr. 1999.

[10] D.L. Donoho, “De-Noising by Soft-Thresholding,” *IEEE Transactions on Information Theory*, Vol. 41, No. 3, May 1995.

[11] M. Hashemi, S. Beheshti, “Adaptive Noise Variance Estimation in BayesShrink,” *IEEE Signal Processing Letters*, Vol. 17, No.1, January 2010.

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