Iterative Edge-Preserving Adaptive Wiener Filter for Image Denoising

Chikako Abe and Tetsuya Shimamura

***Abstract*—In this paper, an image denoising method for noisy image corrupted by additive white noise is proposed. It is well known that the Adaptive Wiener Filter (AWF) is suitable for such denoising. However, some noises remain in the image processed by AWF. In order to improve the performance of the AWF, an iterative algorithm is derived. To prevent original image signal loss, a weighting parameter is used for the noise variance estimate and a technique adjusting the filter kernel is employed. Compared to the conventional AWF, the proposed filter provides better edge performance.**

***Index Terms*—Component; image denoising, wiener filter, iterative algorithm, edge**

I. Introduction

Image denoising of a degraded image corrupted by additive noise is important in the field of image processing. An image has a variety of information such as edge and plane regions, thus a powerful noise reduction with keeping the original image signal is desired. In this paper, we consider denoising of an image corrupted by additive white Gaussian noise. The Adaptive Wiener Filter (AWF) is a popular denoising method for additive white Gaussian noise [1]. The AWF uses the central pixel value and local statistical value, therefore the filtering process is adaptive, resulting in a high quality restored image. However, the statistical values calculated within a limited local window are less reliable, because a local window is too small for the extraction of accurate statistical characteristics from a noisy image [2]. If the degraded image is of low Signal-to-Noise Ratio (SNR), some noises remain in the image processed by the AWF, because the estimated noise value is far from the correct one. On the other hand, if the degraded image is of high SNR, the edge components become too smooth in the image processed by the AWF. This means that the original image information is distorted. The aim of this paper is to solve these problems the AWF processes by improving the performance of the AWF. We propose an Iterative Adaptive Wiener Filter (IAWF) to solve the remaining noise problem. There are some iterative methods for denoising which rely on the use of the Wiener filter, such as [3]. However, these methods need to obtain the original image information, that is impossible in practice in blind condition. Our method is based on the AWF, and uses only the given noisy image. The use of an iterative operation makes the edge components smoothing, thus we consider the design of filter coefficients to preserve edge parts for the purpose of improving the performance of the AWF.

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The authors are with School of Science and Engineering, Saitama University, Shimo-Okubo 255, Sakura-ku, Saitama, 338-8570, Japan (e-mail: abe@sie.ics.saitama-u.ac.jp, shima@sie.ics.saitama-u.ac.jp)

This paper is organized as follows. Section II describes the AWF algorithm and develops its iterative version, IAWF. Some experimented results are shown where the AWF and IAWF are compared. Section III introduces an edge preserving technique for the AWF. Section IV derives the proposed filter and shows preliminary experimental results to optimize the parameter setting. In Section V, we compare the performance of the proposed method with the conventional ones, and in Section VI we conclude the paper.

II. The Adaptive Wiener Filter Algorithm

A. Degraded Image Model

The degraded image y is assumed to be

$$y = x + n \tag{1}$$

where x is the original image and n is a zero mean additive white Gaussian noise whose standard deviation is σ_n.

B. The Adaptive Wiener Filter

The AWF is expressed by the following equations:

$$\hat{x}(i,j) = \frac{\sigma_x^2(i,j)\cdot y(i,j) + \sigma_n^2 \cdot \bar{y}(i,j)}{\sigma_x^2(i,j) + \sigma_n^2} \tag{2}$$

$$\sigma_x^2(i,j) = \max\{0, \sigma_y^2(i,j) - \sigma_n^2\} \tag{3}$$

where $\hat{x}(i,j)$ is the filtered output at (i, j), σ_n^2 is the noise variance which is constant over the image, and $\bar{y}(i,j)$ and $\sigma_y^2(i,j)$ are the local mean and local variance of the input image y at (i, j). The output is calculated using the central pixel value and local statistics, it means that the filtering process is not constant for each pixel. The AWF provides a good performance for the degraded image corrupted by additive white Gaussian noise.

However, if the SNR of the degraded image is low, remaining noises appear in the restored image. Hence, the performance quality by the AWF is limited.

C. The Iterative Adaptive Wiener Filter

In a low SNR case, the AWF performance is limited as mentioned above. Therefore if the remaining noise is more effectively reducted, the denoising performance will be more improved. From this point of view, we propose the IAWF to reduce the remaining noise more by utilizing the AWF.

The IAWF is a simple method, in which the AWF is only iterated. Using the iterative approach, the remaining noise components can be more reduced than only the use of the non-iterative AWF. The difference between the AWF and the IAWF is not only iteration. We change the part of variance σ_n^2 in (2) to $\alpha\times\sigma_n^2$, as described below, where α is an adjustment parameter.

An iterative operation makes the restored image smooth, as a result, we cannot avoid to make the restored image blur. In the AWF, the noise variance σ_n^2 is directly associated with this problem. If σ_n^2 is small (low noise level case), the output pixel value using the AWF is nearly equivalent to the input pixel value. If σ_n^2 is large (high noise level case, except for that $\sigma_y^2 - \sigma_n^2$ is negative), the output pixel value nearly approaches to the average of the input pixel values within a local window. If the estimated value σ_n^2 is too far from the true value, the filtered image becomes too blurred, and the denoising performance cannot be better. To avoid such a too smoothing problem, we multiply the noise variance by an adjustment parameter α as

$$\hat{x}_t(i,j) = \frac{\sigma_{t,x}^2(i,j)\cdot y_t(i,j) + \alpha\sigma_{t,n}^2\cdot \bar{y}_t(i,j)}{\sigma_{t,x}^2(i,j) + \alpha\sigma_{t,n}^2} \tag{4}$$

$$\sigma_{t,x}^2(i,j) = \max\{0, \sigma_{t,y}^2(i,j) - \alpha\sigma_{t,n}^2\} \tag{5}$$

where the parameter t indicates the iteration number. The filtering process of the IAWF becomes equal to the AWF when $t = 1$ and $\alpha = 1$. The filtering performance of the IAWF depends on the parameters t and α. The values of t and α should be changed according to the noise level included in the image.

1) Optimization of parameters

Combination of the iteration number t and the adjustment parameter α is affected by the SNR of the degraded image when we implement the IAWF. Here, we simulate which parameter combination is appropriate for the IAWF.

The simulation condition is as follows. Images are obtained from SIDBA, 256 × 256 size gray scale images and they are corrupted by additive white Gaussian noise, resulting in SNR= 0, 5, 10, 15[dB]. The parameter α is adjusted for 0.1 ~ 1.5 and the iteration number t is done for 1 ~ 10, with the increment of 0.1. The mean value of the results at each SNR was calculated 100 times, and the best combination of the parameters was found for individual noise generation. To evalate the performance easily, we used the Peak-Signal-to-Noise-Ratio (PSNR) defined as

$$\text{MSE} = \frac{1}{M^2}\sum_{i=1}^{M}\sum_{j=1}^{M}\{x(i,j) - \hat{x}(i,j)\}^2 \tag{6}$$

$$\text{PSNR} = 10\log_{10}\left(\frac{S_{MAX}^2}{\text{MSE}}\right). \tag{7}$$

where S_{MAX}^2 is the max value of the image signal, which is 255 here.

Fig. 1 shows the simulation results. In Fig.1, each point indicates a combination of t and α which produces the highest PSNR value of IAWF. One point corresponds to one image processing result. The results in Fig.1 show that the best combination of t and α is not unique, that is different for every image. However, there is a similarity for the specified SNR. That is, if the noise level is high, the t and α are large. On the other hand, if the noise level is low, the t and α are small. We calculated the average at each SNR and decided an appropriate combination value at each SNR. Table I shows the result.

2) Performance Comparison of AWF and IAWF

We compare the AWF with the IAWF here.

The parameters for the IAWF are given in Table I. Table II shows PSNRs obtained on BOAT image. Table II suggests that the IAWF is better than the AWF. Figure 2 shows images processed by the AWF and IAWF, respectively. Figure 2 suggests that the IAWF could reduce the remaining noise more effectively than the AWF.

However, the IAWF reduces noise heavily, resulting in some small edges being different from the original image. In fact, the IAWF is a too smoothing filter and destroys the original edge components sometimes. To the preserve edge components and effectively reduce noise, an edge-preserving Wiener filter is introduced in the next section.

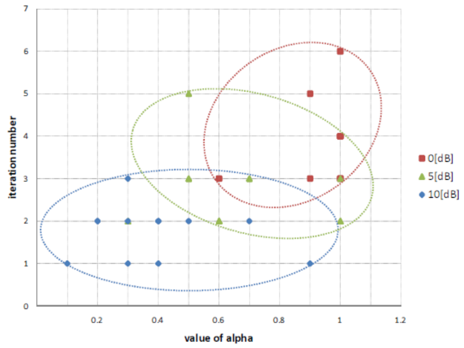
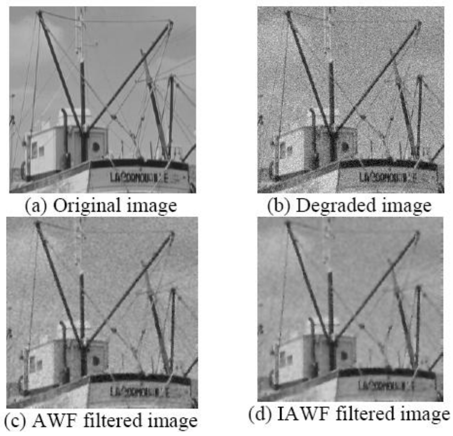


Fig.1. Distribution map (SNR = 0, 5, 10[dB])

TABLE I: COMBINATION TOF THE ITERATION NUMBER t AND ADJUSTMENT PARAMETER W.R.T. NOISE REVEL FOR IAWF

SNR[dB]	*t*	□
0	4	0.9
5	3	0.6
10	2	0.3
15	1	0.1



(a) Original image (b) Degraded image (c) AWF filtered image (d) IAWF filtered image

Fig. 2. Processed BOAT images (SNR=5).

III. EDGE-PRESERVING WIENER FILTER

In [2], the authors have presented a resolution enhancement algorithm based on modified Wiener filtering, which is called Modified Wiener Filter, where the resolution enhancement is achieved by properly adjusting the filter kernel of the conventional AWF. This method classifies the plain and edge regions based on the local variance and noise variance. For the plane region, the AWF is simplified with

TABLE II: PSNR RESULTS BY AWF AND IAWF ON BOAT IMAGE

	SNR 0 [dB]		SNR 5 [dB]		SNR 10 [dB]		SNR 15 [dB]	
Image	***AWF***	***IAWF***	***AWF***	***IAWF***	***AWF***	***IAWF***	***AWF***	***IAWF***
Boat	24.492	25.993	28.574	28.725	31.460	31.972	33.076	34.848

$$\sigma_n^2 \geq \sigma_y^2(i,j) \rightarrow \sigma_x^2(i,j) = 0 \quad (8)$$

as

$$\hat{x}(i,j) = \bar{y}(i,j). \quad (9)$$

For the edge region, the AWF is replaced with

$$\sigma_n^2 < \sigma_y^2(i,j) \rightarrow \sigma_x^2(i,j) = \sigma_y^2(i,j) - \sigma_n^2 \quad (10)$$

by

$$\begin{aligned}\hat{x}(i,j) &= \left(1 - \frac{\sigma_n^2}{\sigma_y^2(i,j)}\right)\cdot y(i,j) + \frac{\sigma_n^2}{\sigma_y^2(i,j)}\cdot \bar{y}(i,j)\\ &= (1-r)\cdot y(i,j) + r\cdot \bar{y}(i,j)\\ &= c_1 \cdot y(i,j) + c_2 \cdot \bar{y}(i,j)\end{aligned} \quad (11)$$

where c_1 and c_2 are the filter coefficients of the conventional Wiener filter. For the plain region, c_2 is larger than c_1, and for the edge region, c_1 is larger than c_2. However, due to a limited local window, the estimated statistical values, such as the local variance, are less reliable. As a result, pixels that are actually among a part of the plain region, can be classified as a part of the edge region. In [2], to solve this problem, the modified Wiener filter is used which controls the filtering power for the edge region based on the following change:

$$\begin{aligned}\hat{x}(i,j) &= (1 - f(r))\cdot y(i,j) + f(r)\cdot \bar{y}(i,j)\\ &= p_1 \cdot y(i,j) + p_2 \cdot \bar{y}(i,j)\end{aligned} \quad (12)$$

where $f(r)$ is defined as $e^{-1/rk}$, k is the scale factor for the adjustment, and p_1 and p_2 are the filter coefficients of the modified Wiener Filter. In [2] it has been shown that as k increases, the filtering power also increases. Due to insufficient the edge preserving of the conventional Wiener filter, noises are ineffectively eliminated and the remaining ones appear as spikes in the filtered image. Therefore, to reduce these noises, the modified Wiener filter increases the filtering power in the edge region by modifying the filter coefficients of the conventional Wiener filter in a fashion to preserve the edges.

IV. PROPOSED METHOD

From Sections II and III, it is clear that the IAWF is effective for the remaining noise reduction, and the modified Wiener Filter can preserve edge components. From this point of view, to improve more the Wiener Filter performance, we propose the Iterative Modified Wiener Filter (IMWF) here.

The IMWF is described as

$$\hat{x}_t(i,j) = \frac{\sigma_{t,x}^2(i,j)\cdot y_t(i,j) + \alpha\sigma_{t,n}^2 \cdot \bar{y}_t(i,j)}{\sigma_{t,x}^2(i,j) + \alpha\sigma_{t,n}^2} \quad (13)$$

$$\sigma_{t,x}^2(i,j) = \max\{0, \sigma_{t,y}^2(i,j) - \alpha\sigma_{t,n}^2\} \quad (14)$$

where t is the iteration number and α is the adjustment parameter for iterations. From (12), in the edge region the processing becomes

$$\begin{aligned}\hat{x}_t(i,j) &= (1 - f(r_t'))\cdot y_t(i,j) + f(r_t')\cdot \bar{y}_t(i,j)\\ &= p_1 \cdot y_t(i,j) + p_2 \cdot \bar{y}_t(i,j)\end{aligned} \quad (15)$$

and

$$f(r) = e^{-1/(r_t'k)}, \quad r = \frac{\alpha\sigma_{t,n}^2}{\sigma_{t,y}^2(i,j)}. \quad (16)$$

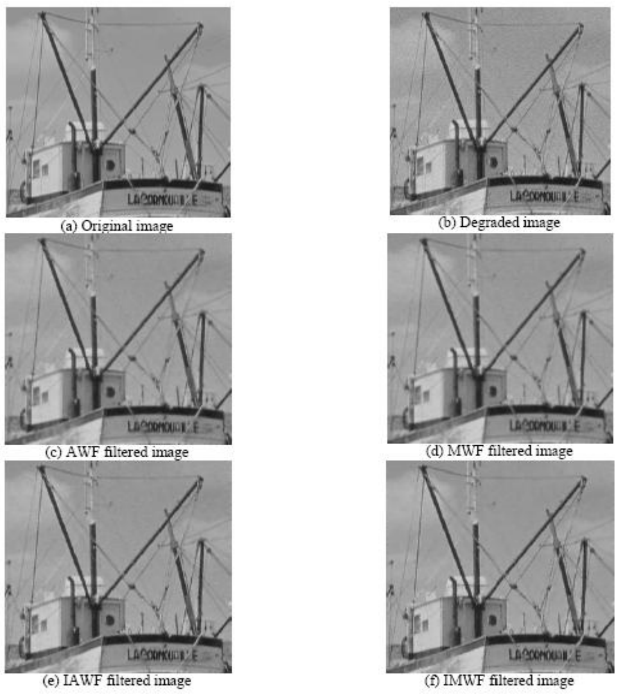


Fig. 3. Denoising images BOAT (SNR = 15 [dB]).

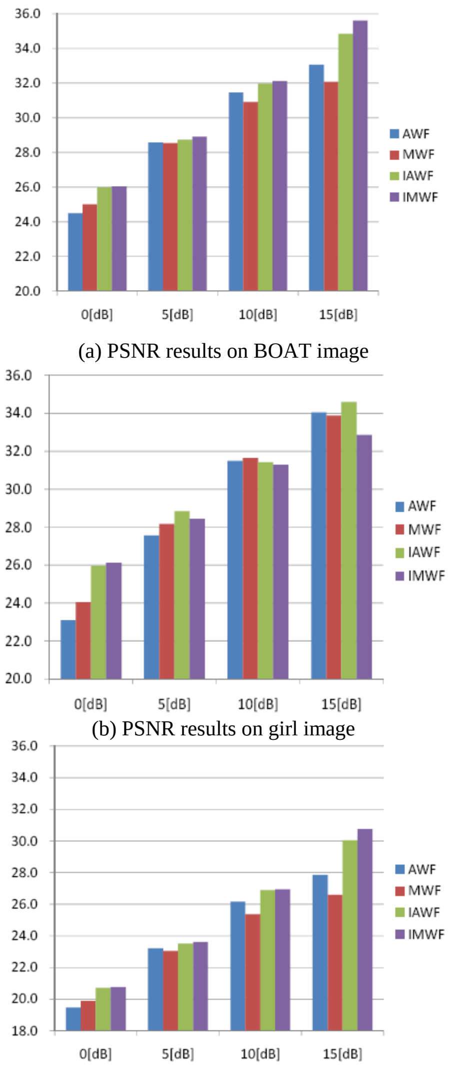
A. Preliminary Experiment

The best combination of the iteration number t and adjustment parameter α for the IMWF may be different from that for the IAWF. Thus, the best combination for the IMWF was found in a similar way conducted in Section II.

The experimental conditions are the same as these in Section II-C1. In Addition, the parameter k is adjusted for 1 ~ 15. The mean value at each SNR was calculated for individual 100 times noise generation. Table III shows the result. In Table III, the parameter k has been also optimized.

TABLE III : COMBINATION OF THE ITERATION NUMBER t , ADJUSTMENT PARAMETER α, AND SCALE FACTOR k FOR IMWF.

SNR[dB]	*t*	α	*k*
0	4	0.9	3.8
5	2	0.6	6.5
10	2	0.3	13.2
15	6	0.1	15.0



(a) PSNR results on BOAT image

(b) PSNR results on girl image

(c) PSNR results on airplane image

Fig. 4.

V. DENOISING RESULTS BY IMWF

B. Experimental Conditions

To show the effectiveness of the IMWF, a performance comparison between the AWF, MWF, IAWF, and IMWF was conducted. The parameters for the IMWF are those in Table III. Each evaluation is the mean value of PSNRs for 100 independent trials.

C. Experimental Results

Fig. 4 shows the PSNRs obtained on BOAT, Girl, and Airplane images. An example of the restored images on BOAT in case of SNR=15[dB] is shown in Figure 3.

We obtained from the results on the BOAT image and the Airplane image the fact that both iterative methods are superior to the MWF. It seems that the remaining noises have been effectively reduced using an iterative process. However, the IMWF performance is not always superior to the conventional methods, as shown in Fig.4 (b) where the IMWF performances are lower than the others.

VI. CONCLUSION

In this paper, we have proposed an iterative edge preservation Wiener Filter. The proposed method could reduce the remaining noise more effectively and preserve some small edges than the other conventional methods.

However, the best parameter setting for the proposed method is different for images. By more appropriate setting of the parameters, a further performance improvement will be expected.

REFERENCES

[1] J. S. Lim, "Two-Dimensional Signal and Image Processing," Prentice-Hall, 1990.

[2] Y. Song and D. Choi, "Kernel Adjusted Wiener Filter for Image Enhancement," *Japanese Journal of Applied Physics*, vol. 44, no. 6A, pp. 3996－3999, 2005.

[3] P. L. Chin and S. D. Morgera, "Iterative Methods for Restoring Noisy Images," *IEEE Transactions on Acoustics*, Speech, and Signal Processing, vol. 37, no. 4, 1989.

[4] H. C. Andrews and B. R. Hunt, "Digital Image Restoration," *Prentice-Hall*, 1977.

[5] T. Kobayashi and T. Shimamura, "Restoration from Image Degraded by White Noise Based on Iterative Spectral Subtraction Method," *IEEE International Symposium on Circuits and Systems*, pp. 6268 – 6271, vol. 6, 2005.