ISSN (O) 2321-2004, ISSN (P) 2321-5526

IJIREEICE

International Journal of Innovative Research in Electrical, Electronics, Instrumentation and Control Engineering

Vol. 9, Issue 10, October 2021

DOI: 10.17148/IJIREEICE.2021.91005

Improved Image Denoising Scheme Based On Wavelet Thresholding

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Abstract: Hitherto the methods discussed on image denoising are based on either transform or spatial domain which works on the noisy coefficients and try to minimize the effects of noise and improve the quality of the input. This paper is the step towards that, the method proposed here is a transform based wavelet denoising scheme found to improve the performance of the image. The thresholding are done by block matching approach.

Keywords : block matching, wavelet denoising, transform domain

1. INTRODUCTION

Various authors strived to improve the performance of the Wiener filter; however, most studies did not address one persisting problem of the Wiener filter[8,9,11] which is it uses a function which is objective in nature referred as mean square error (MSE), however it is possible to use a better measure than MSE [12.,13] as the function of Wiener filter. Also, if the Wiener filter is improved, the performance of denoising which is based on the said filter can also be improved, of its. In the approach proposed, we will primarily focus on the improvement of Wiener filter. Then, we will use this improved filter function to enhance the associated performance of denoising engine.

2. BLOCK MATCHING FILTERING

The proposed block matching filtering algorithm [6,7,14] is best described by the block diagram shown in Figure 1. The first step of the filter proposed starts its operation by dividing noisy observation into number of blocks or patches. The next step is to perform the transform on the noisy patches which is required step to convert the spatial domain information to frequency domain. The important part after the transformation is to filter and threshold the noisy coefficients and retaining the signal content. Soon after the wavelet thresholding the inverse wavelet transform is done to convert back to spatial domain. The next procedure is block wise matching this step is required to accurately estimate the observation and then to a denoised image. Worth noting point here is the choice of wavelets any symmetrical wavelet [1,2,3,4]could be used we have used daubechies with 6 vanishing moments.

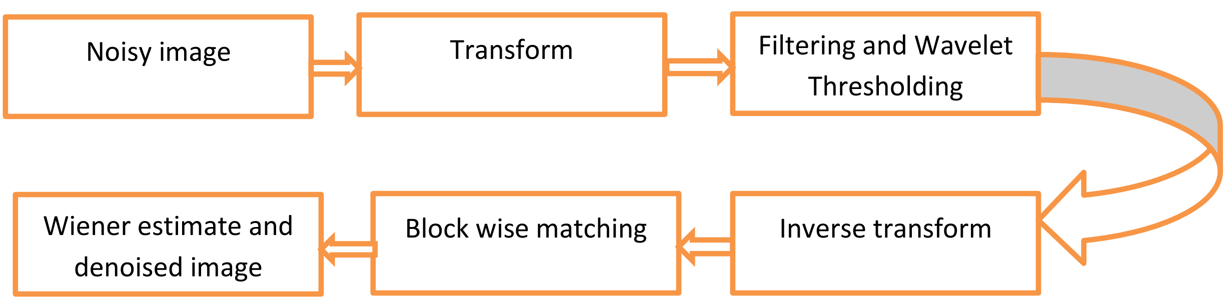

Figure 1 block diagram of proposed method

$$\varpi = \frac{\left\|\tau^{wien}(P)\right\|}{\left\|\tau^{wien}(P)+\sigma^{2}\right\|}\tau^{wienfinal}(P). \qquad (1)$$

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The final denoised image estimate is calculated by using equation [5,10] 1 where is the basic estimate, is the final estimate which is used as moderation parameter for final denoising.

3. RESULTS AND DISCUSSIONS

The experimental observation are done on gray scale Lena image of size 512×512 and also used Barbara image of similar size. The performance parameter is used to gauge the performance of the method. The results are shown for Lena image by table 1 and by figure 2. And for the Barbara image table2 and figure 4. By observing the results as it is compared with BM3D algorithm the proposed method outperforms the published method its percentage improvement is also listed in the tables.

Table 1 denoised image Lena of size 512×512

Variance	Noisy image PSNR	BM3D PSNR	Proposed method PSNR	PSNR gain	PSNR gain%
10	28.1353	34.1700	35.9274	1.7574	5.1431
15	24.6135	32.1800	34.2716	2.0916	6.4997
20	22.1147	31.0900	33.0510	1.9610	6.3075
25	20.1765	30.0020	32.0775	2.0755	6.9179
30	18.5929	29.2700	31.2621	1.9921	6.8059
35	17.2539	28.0001	30.5648	2.5647	9.1596
40	16.0941	27.9100	29.8647	1.9547	7.0036
45	15.0711	27.5020	29.5139	2.0119	7.3155
50	14.1559	27.0600	29.0503	1.9903	7.3551
55	13.3281	26.5600	28.6455	2.0855	7.8520
60	12.5723	26.3000	28.2710	1.9710	7.4943

Table 2 denoised image Barbara of size 512×512

Variance	Noisy image PSNR	BM3D PSNR	Proposed method PSNR	PSNR gain	PSNR gain%
10	28.1353	33.3689	34.9763	1.6074	4.8171
15	24.6135	31.1226	33.1142	1.9916	6.3992
20	22.1147	29.8272	31.7782	1.9510	6.5410
25	20.1765	28.5419	30.7174	2.1755	7.6221
30	18.5929	27.8215	29.8136	1.9921	7.1603
35	17.2539	27.4185	28.9832	1.5647	5.7067
40	16.0941	26.0361	27.9908	1.9547	7.5077
45	15.0711	25.7505	27.7624	2.0119	7.8131
50	14.1559	25.2350	27.2253	1.9903	7.8871
55	13.3281	24.7460	26.7315	1.9855	8.0235
60	12.5723	24.3088	26.2798	1.9710	8.1082

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Figure 2 results obtained by using 512×512 Lena image

$$\begin{bmatrix} a & b & c \\ d & e & f \\ g & h & i \end{bmatrix}$$ a=10, b=15,c=20,d=25,e=30,f=35,g=40,h=50,i=60 variances respectively

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Figure 3 results obtained by using 512×512 Barbara image

$\begin{bmatrix} a & b \\ c & d \\ e & f \end{bmatrix}$ a=10, b=20,c=30,d=40,e=50,f=60 variances respectively.

4. CONCLUSION

The following conclusions are drawn from the results obtained after the rigorous enforcement we have found that the results of the proposed method is outperform the results of the existing method, further to prevent the loss of clarity, an adaptive classification can be looked in to enhance the results of the proposed

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