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Image Processing for Denoising Using Composite Adaptive Filtering Methods Based on RMSE

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Abstract

As one of the carriers for human communication and interaction, images are prone to contamination by noise during transmission and reception, which is often uncontrollable and unknown. Therefore, how to denoise images contaminated by unknown noise has gradually become one of the research focuses. In order to achieve blind denoising and separation to restore images, this paper proposes a method for image processing based on Root Mean Square Error (RMSE) by integrating multiple filtering methods for denoising. This method includes Wavelet Filtering, Gaussian Filtering, Median Filtering, Mean Filtering, Bilateral Filtering, Adaptive Bandpass Filtering, Non-local Means Filtering and Regularization Denoising suitable for different types of noise. We can apply this method to denoise images contaminated by blind noise sources and evaluate the denoising effects using RMSE. The smaller the RMSE, the better the denoising effect. The optimal denoising result is selected through comprehensively comparing the RMSE values of all methods. Experimental results demonstrate that the proposed method effectively denoises and restores images contaminated by blind noise sources.

Keywords

Blind Denoising, Adaptive, RMSE, Image Restoration

1. Introduction

Images serve as a vital means for human interaction and communication, providing a visual description and representation of objective entities. With the advancement of technology, image processing techniques have garnered significant attention and research due to the crucial role of images as carriers of information. In practical scenarios, the transmission and reception of images face numerous challenges, with noise interference being one of the most prevalent. For instance, in astronomical observations, signals received by space telescopes often contain substantial noise, which hampers scientific research. Similarly, in the medical field, medical images can suffer from reduced clarity due to environmental factors, thereby impacting healthcare professionals' ability to assess patients' conditions accurately.

Therefore, researching image restoration techniques that are robust to noise interference hold significant importance for practical applications. Among various tasks in image restoration, denoising stands out as the most fundamental and crucial one.

Currently, denoising techniques can be broadly classified into two categories: traditional denoising algorithms and deep learning-based denoising algorithms. Traditional denoising algorithms primarily operate in the spatial domain and transform domain, including filtering algorithms such as Mean Filtering, Median Filtering, Discrete Wavelet Transform [1]-[7], as well as variational models like K-SVD [8] sparse representation algorithm, WNNM cluster low-rank algorithm, HMM statistical model algorithm, TV denoising algorithm, etc. On the other hand, deep learning-based denoising algorithms include networks like DnCNN [9], FFDNET [10], MIRNET [11], Neighbor2Neighbor [12] self-supervised network, etc. As the era progresses, various improved methods have been proposed to meet the needs of the current context. For instance, to enhance denoising performance, MAGGIONI *et al.* [13] introduced an improved denoising algorithm that constructs a four-dimensional group cube and utilizes local and non-local correlations of the cube, employing coefficient shrinkage algorithm for signal and noise separation. SCEIBON *et al.* proposed the Deep K-SVD algorithm, which transforms the K-SVD denoising model into a learnable architecture, enabling backpropagation and improving denoising performance. However, these data-driven denoising algorithms require a large amount of training data, and they often exhibit significant performance degradation when there are differences between the training and testing data. In practical applications, obtaining a large amount of training data is often not feasible.

While these algorithms can achieve denoising results, they are typically designed for scenarios where the noise is known or the object is affected by a single type of noise. The effectiveness of these algorithms varies when dealing with images contaminated by different types of noise or mixed noise, which differs from the noise studied in their development. In practical applications, most image noise is unknown and may even consist of multiple types, posing limitations on the above methods. Furthermore, due to the lack of prior knowledge, evaluating the denoising and restoration of images becomes a challenging task. Hence, the focus of current research and one of the objectives of this paper is how to denoise and restore images affected by blind or unknown mixed noise.

Common types of noise include salt-and-pepper noise, Gaussian noise, Poisson noise, multiplicative noise, etc. Traditional denoising algorithms such as mean filtering, median filtering, Gaussian filtering (GF), non-local means filtering (NMF), bilateral filtering (BF), etc., compared to BM3D and other deep learning algorithms, have less computation time and better performance in processing single noise types. However, different traditional denoising algorithms have varying effects on different types of noise. For example, mean filtering has a certain suppression effect on various types of noise, with the best performance in handling salt-and-pepper noise; Gaussian filtering is very effective in dealing with Gaussian noise; non-local means filtering, despite having better overall denoising effects compared to other methods, has higher computational complexity and longer processing time due to its multiple parameters, including window radius and control of the search window size, and the degree of filtering also determines the denoising effect; bilateral filtering is a nonlinear filtering method that balances spatial proximity and pixel value similarity in image processing, achieving edge-preserving denoising while ensuring a certain level of edge information. Bilateral filtering has a certain suppression effect on various types of noise, but compared to traditional methods such as mean filtering, bilateral filtering has longer processing time. In summary, different filtering methods have their own advantages and disadvantages, and they are targeted differently. How to accurately denoise and restore images affected by blind noise is one of the problems that need to be addressed.

In addition, traditional metrics for evaluating image denoising effectiveness, such as Peak Signal-to-Noise Ratio (PSNR) and Structural SIMilarity (SSIM), are both based on the assumption of having the original image known. Mean Structural SIMilarity (MSSIM) is applicable only to hyperspectral images and not suitable for blind noise evaluation. Therefore, proposing new evaluation criteria is also one of the problems that need to be addressed. Blind denoising and restoration of images involve various challenges, often stemming from factors such as unknown types and numbers of noise, model selection and parameter tuning, computational complexity, and evaluation criteria. Addressing these issues, this paper proposes a method for image processing based on Root Mean Square Error (RMSE) integrated with multiple adaptive filtering techniques for denoising. Compared to other traditional algorithms，the proposed method can not only deal with a variety of noises, but also with blind noise sources. And it has corresponding evaluation indexes to verify the effect of denoising.

2. The Proposed Method

The method for image processing based on RMSE by integrating multiple adaptive filtering methods for denoising, integrates multiple adaptive filtering techniques for denoising images. It primarily leverages various traditional denoising methods such as wavelet filtering, Gaussian filtering, median filtering, mean filtering, bilateral filtering, adaptive bandpass filtering, non-local means filtering, and regularization denoising [1]-[7].

The core idea of this method is to denoise the blind noise sources using each of the aforementioned methods separately. Then, based on the evaluation values proposed in this paper, the parameter values of each method are adjusted to achieve the optimal denoising effect. Finally, all denoising results are comprehensively compared, and the best one is selected as the final denoised result. Before presenting the flow of the proposed method, we first review the theory of these classical methods. The theoretical framework of the method is as follows:

2.1. Wavelet Filtering

Wavelet transform provides the capability to analyze and process local features of an image by decomposing it into wavelet coefficients of different scales and frequencies. It effectively addresses the problem of frequency variation in non-stationary signals.

The original image $I(x, y)$ is decomposed using wavelet transform to obtain wavelet coefficients at different scales and orientations. The process of wavelet decomposition can be represented as:

$$C_{a,b} = \sum_x \sum_y I(x, y) \cdot \Psi_{a,b}(x, y) \tag{1}$$

In wavelet coefficients, high-frequency components are often affected by noise. Thresholding the wavelet coefficients can remove smaller coefficients, thereby reducing the influence of noise. Thresholding can be performed using hard thresholding or soft thresholding, with the formulas as follows:

$$C_{thresh}(a,b) = \begin{cases} 0, & \text{if } \left|C_{a,b}\right| < \lambda \\ C_{a,b}, & \text{otherwise} \end{cases} \tag{2}$$

where $C_{thresh}(a,b)$ represents the wavelet coefficients after thresholding, and λ is the threshold parameter.

Perform an inverse wavelet transform on the wavelet coefficients after thresholding to obtain the denoised image. The process of inverse wavelet transform can be represented as:

$$\hat{I}(x, y) = \sum_x \sum_y C_{thresh}(a,b) \cdot \Psi_{a,b}(x, y) \tag{3}$$

where $\hat{I}(x, y)$ represents the denoised image.

2.2. Gaussian Filtering

Gaussian filter is a linear smoothing filter that selects weights according to the shape of the Gaussian function. Whether in the spatial domain or in the frequency domain, Gaussian smoothing filter is an effective low-pass filter, especially for removing noise following a normal distribution. Therefore, it has broad prospects in image processing. For a zero-mean one-dimensional Gaussian function, it can be represented as:

$$f(x) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2}{2\sigma^2}} \tag{4}$$

where the Gaussian distribution parameter σ determines the width of the Gaussian function. When processing images, the zero-mean two-dimensional discrete Gaussian function is commonly used as a smoothing filter, and the corresponding function expression is:

$$f(i,j)=\frac{1}{2\pi\sigma^2}\mathrm{e}^{-\frac{i^2+j^2}{2\sigma^2}} \tag{5}$$

The size of the variance σ^2 significantly affects the weighting of the Gaussian template. If σ^2 is too small, the weights of non-central pixel points are very small, and the influence of the neighborhood in the filtering process is almost ignored. The neighborhood operation degenerates into point-wise operation on the image, failing to achieve denoising effects. If σ^2 is too large, Gaussian filtering degenerates into a mean template, leading to the loss of image details. Therefore, selecting an appropriate value for σ^2 is crucial for denoising pixel values while preserving the details of the image.

2.3. Median Filtering

The main idea of median filtering is to sort the pixel values in the neighborhood of a certain pixel according to their magnitudes, and then select the middle value to replace the pixel value of that point. Now, consider a one-dimensional sequence: f_1, f_2, …, f_n undergoing median filtering. Let the window length be m, where m is an odd number. Then, from this sequence, we extract m values: f_{i-v}, …, f_i, …, f_{i+v}, where f_i is the median value of this window and $v=\frac{m-1}{2}$. Afterwards, these m values are sorted according to their magnitudes, and the middle value is chosen as the pixel value of that point. The mathematical expression is as follows:

$$y_i = Med\left\{f_{r-v}\wedge f_i\wedge f_{i+v}\right\}\quad i\in Z\quad v=\frac{m-1}{2} \tag{6}$$

$$Y_{i,j}=Med\left\{y_{ij}\right\}$$

where m is the window size. Median filtering can effectively overcome image blurring.

2.4. Mean Filtering

Mean filtering smooths an image and reduces noise by calculating the average pixel value within a local region of the image. The basic idea of mean filtering is to replace the value of each pixel with the average value of the pixel values in its surrounding neighborhood. This operation reduces the impact of noise on the image but may also result in blurring of image details. Mean filtering is commonly used to remove mild noise, but it may not be effective for images with significant noise.

Let the input image be denoted as $I(x,y)$, where x and y are spatial coordinates of the image. The basic step of mean filtering is to compute the average pixel value within a local neighborhood of each pixel in the image and use that average value as the filtered pixel value. The local neighborhood can be defined by an $N \times N$ window, where N is an odd number typically chosen as 3, 5, 7, etc. Thus, the formula for mean filtering at coordinate (x, y) can be expressed as:

$$\hat{I}(x, y) = \frac{1}{N^2} \sum_{i=-\frac{N-1}{2}}^{\frac{N-1}{2}} \sum_{j=-\frac{N-1}{2}}^{\frac{N-1}{2}} I(x+i, y+j) \tag{7}$$

where $\hat{I}(x, y)$ represents the filtered pixel value, and $I(x+i, y+j)$ denotes the pixel values located within the window.

2.5. Bilateral Filtering

Bilateral filtering preserves edge information while smoothing the image. It smooths the image based on the similarity and distance between pixels, reducing the influence of noise while preserving the edge details of the image.

Assuming the input image is $I(x, y)$, where x and y are spatial coordinates of the image. The formula is as follows:

$$\hat{I}(x, y) = \frac{1}{W_p} \sum_{x', y'} I(x', y') \cdot w_s \cdot w_r \tag{8}$$

where W_p is the sum of normalized weights, expressed as:

$$W_p = \sum w_s \cdot w_r \tag{9}$$

where w_s represents the weight based on pixel value similarity, and w_r represents the weight based on spatial distance, expressed as:

$$w_s = \mathrm{e}^{-\frac{(I(x', y') - I(x, y))^2}{2\sigma_s^2}}$$

$$w_r = \mathrm{e}^{-\frac{\|(x', y') - (x, y)\|^2}{2\sigma_r^2}} \tag{10}$$

where σ_s and σ_r are parameters used to control the similarity and distance weights, respectively. These weights allow pixels that are farther away or have larger differences in pixel values to contribute less to the average, thereby preserving edge information.

2.6. Adaptive Bandpass Filtering

Adaptive Bandpass Filtering (ABF) adjusts filter parameters adaptively to retain useful information within a certain frequency range while suppressing noise. This method is suitable for removing noise within specific frequency ranges in an image while preserving details.

Assuming our input image is $I(x, y)$, where x and y are the spatial coordinates of the image. The basic idea of adaptive bandpass filtering is to filter the image in the frequency domain. First, the Fourier transform of the image needs to be performed:

$$F(u, v) = F\{I(x, y)\} \tag{11}$$

where u and v are frequency coordinates. The bandpass filter $H(u,v)$ is given by the following equation:

$$H(u,v) = \begin{cases} 1, & \text{if } D_{low} \le D(u,v) \le D_{high} \\ 0, & \text{otherwise} \end{cases} \tag{12}$$

where $D(u,v)$ is the distance in frequency coordinates, representing the distance from the center frequency. D_{low} and D_{high} are the lower and upper limits of the frequency range.

The filtered spectrum $G(u,v)$ is obtained by applying the filter to the image in the frequency domain:

$$G(u,v) = F(u,v) \cdot H(u,v) \tag{13}$$

Adaptive bandpass filtering requires determining the frequency range of D_{low} and D_{high} based on the spectral characteristics of the image, thus better preserving the useful information in the image.

2.7. Non-Local Means Filtering

Non-local means filtering reduces noise by utilizing information from similar pixels across the entire image. Unlike local filtering methods, non-local means filtering can find similar pixels over a larger range, thereby preserving more details while smoothing the image.

Assuming our input image is $I(x,y)$, where x and y are the spatial coordinates of the image.

$$\hat{I}(x,y) = \frac{1}{W_p} \sum_{x',y'} I(x',y') \cdot w(x',y') \tag{14}$$

where W_p represents the sum of normalized weights, expressed as:

$$W_p = \sum w(x',y') \tag{15}$$

where $w(x',y')$ represents the similarity weight between pixel (x',y') and the target pixel (x,y), calculated by the following formula:

$$w(x',y') = \mathrm{e}^{-\frac{1}{h^2}\sum_{i=-p}^{p}\sum_{j=-p}^{p}\left(I(x+i,y+j)-I(x'+i,y'+j)\right)^2} \tag{16}$$

where h is a parameter controlling the similarity weight, and p is the radius of the window. More similar pixels receive higher weights, contributing more to the average value of the target pixel.

2.8. Regularization Denoising

The basic idea of Regularization Denoising (RD) algorithms is to suppress noise by introducing regularization terms in the optimization problem to constrain the smoothness and sparsity of the solution. One of the most classic algorithms is Total Variation (TV) regularization. TV regularization is an optimization method used for image denoising, which introduces a total variation term in the objective function to smooth the image and remove noise. The core idea of TV regularization is to find the smoothest (with minimum total variation) image that is consistent with the observed data (noisy image).

Assuming our input image is I and the observed data with noise is f, our goal is to find a smooth image u such that the difference between u and the observed data is minimized, while also minimizing the total variation. The optimization problem of total variation regularization can be formulated as follows:

$$\min_u \frac{1}{2}\|u - f\|^2 + \lambda \cdot \mathrm{TV}(u) \tag{17}$$

where $\|\cdot\|$ denotes a norm, λ is the regularization parameter, and $\mathrm{TV}(u)$ represents the total variation of the image u, which can be expressed as follows:

$$\mathrm{TV}(u) = \sum_{i,j} \sqrt{\left(u_{i+1,j} - u_{i,j}\right)^2 + \left(u_{i,j+1} - u_{i,j}\right)^2} \tag{18}$$

In this optimization problem, the first term represents the residual between the image u and the observed data f while the second term represents the total variation. By adjusting the regularization parameter λ, the balance between smoothness and data fitting can be controlled. By solving this optimization problem, a smooth reconstructed image u can be obtained.

2.9. Root Mean Square Error

The key to blind noise separation lies in the lack of prior knowledge. Among existing methods for image restoration, there are mainly two standards for evaluating the restoration effect: PSNR and SSIM. In addition, scholars have extended these standards to MPSNR and MSSIM for hyperspectral images, calculating PSNR and SSIM separately for different bands and then taking the average. However, these methods are all based on known prior knowledge, assuming that the original image to be restored is known, which is not applicable to this study. Therefore, this paper uses RMSE to measure the denoising effect. The formula for RMSE is as follows:

$$\mathrm{RMSE} = \sqrt{\frac{1}{mn}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}\left[I(i,j) - K(i,j)\right]^2} \tag{19}$$

where I represents the denoised image, K represents the noisy image, and m and n are the dimensions of the images. As shown in the above equation, the smaller the RMSE, the better the denoising effect.

2.10. The Proposed Method

In summary, we propose a method that image processing for denoising using Composite adaptive filtering methods based on RMSE. By selecting appropriate parameter ranges and applying the aforementioned denoising methods to the noisy spectra, we calculate the RMSE to determine the optimal parameter values for denoising. These parameter values are then used for denoising. Finally, we compare the results of all methods and select the optimal denoising outcome. The method flowchart is illustrated in **Figure 1**.

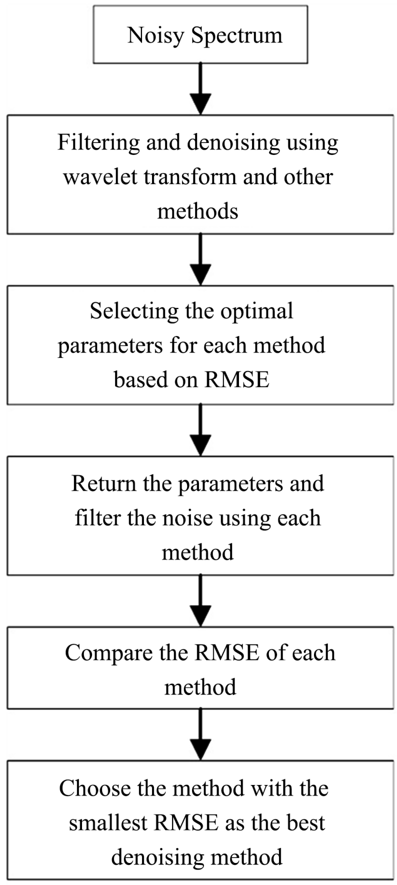

Figure 1. Flowchart of the method.

3. Experiment Verification

Apply the denoising method based on RMSE adaptive filtering to process experimental data. The dataset originates from the 8th Hunan Province Graduate Mathematical Modeling Competition. The dataset consists of spectral data of an image with unknown noise, with a size of 512 × 512. It is obtained by oversampling, magnifying, discrete Fourier transforming, and adding noise to a 256 × 256 image. The noisy spectrum and original image are shown in **Figure 2**.

The best results for each method and their corresponding RMSE values are shown in the following figure and table. For the selection of parameter variables for each method, this study is constrained by three conditions: firstly, to comply with computational constraints; secondly, to ensure consistency in the number of parameter values for ease of visualization and overall observation of RMSE variations; and thirdly, to maximize the variation in RMSE. Parameters are chosen reasonably while satisfying these three conditions.

Figure 3 and **Table 1** show the processing results and RMSE values of wavelet filtering, respectively. It can be seen that when level = 1, the RMSE value is the smallest, indicating the best denoising effect at this level. As the value of level increases, the RMSE gradually increases, which indicates that the denoising effect becomes weaker gradually.

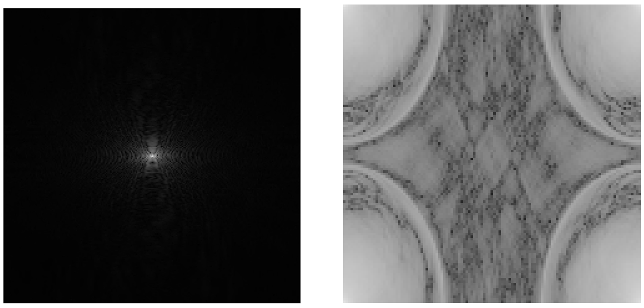

Figure 2. Experimental data spectrum (left) and original image (right).

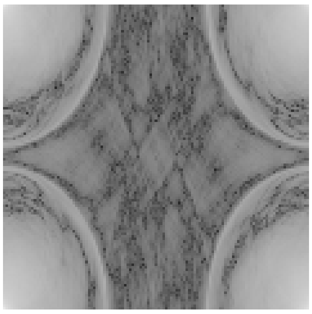

Figure 3. Denoising result with wavelet filtering.

Table 1. RMSE values for wavelet filtering.

level	1	2	3	4	5	6	7	8	9
RMSE	0.0013	0.0017	0.0017	0.0018	0.0018	0.0018	0.0018	0.0018	0.0018

Figure 4 and **Table 2** respectively show the processing results and RMSE values for Gaussian filtering. From the figure, it can be observed that when $\sigma = 0.1$, the RMSE value is the smallest, indicating the best denoising effect. We can get that the RMSE slowly becomes larger as σ increases.

Figure 5 and **Table 3** respectively present the processing results and RMSE values for median filtering. From the figure, it can be observed that when $n = 1$, the RMSE value is the smallest, indicating the best denoising effect. And as n increases, the RMSE becomes larger and more variable than Wavelet Filtering and Gaussian Filtering.

Figure 6 and **Table 4** respectively display the processing results and RMSE values for mean filtering. As shown in the figure, when the filter size is 1, the RMSE value is the smallest, indicating the best denoising effect.

Figure 7 and **Table 5** respectively present the processing results and RMSE values for bilateral filtering. As observed in the figure, when $n = 1200$, the RMSE value is the smallest, indicating the best denoising effect. As can be seen from the **Table 5**, RMSE is less affected by n and does not change much.

Figure 8 and **Table 6** respectively show the processing results and RMSE values for adaptive bandpass filtering. As depicted in the figure, when cutoff = 370, the RMSE value is the smallest, indicating the best denoising effect.

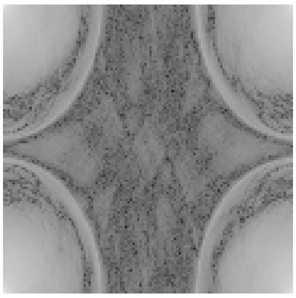

Figure 4. Denoising result with Gaussian filtering.

Table 2. RMSE values for Gaussian filtering.

σ	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
RMSE	0	2.3547×10^{-11}	2.4864×10^{-5}	0.0026	0.0174	0.0423	0.0705	0.1011	0.1333

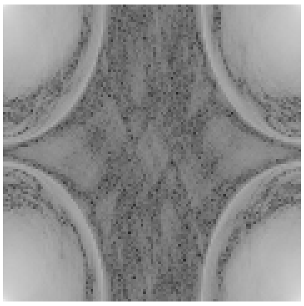

Figure 5. Denoising result with median filtering.

Table 3. RMSE values for median filtering.

n	1	2	3	4	5	6	7	8	9
RMSE	0	0.2501	0.1344	0.3991	0.6162	0.9181	1.2085	1.2916	1.3198

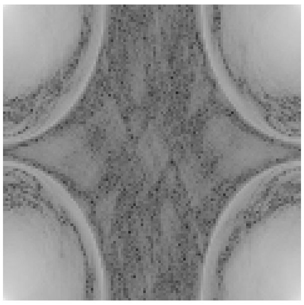

Figure 6. Denoising result with mean filtering.

Table 4. RMSE values for median filtering.

filter_size	1	2	3	4	5	6	7	8	9
RMSE	0	0.2410	0.1385	0.3757	0.4499	0.6588	0.7774	0.9181	1.0087

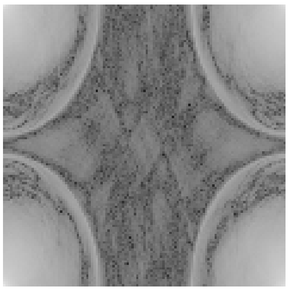

Figure 7. Denoising result with bilateral filtering.

Table 5. RMSE values for bilateral filtering.

n	400	500	600	700	800	900	1000	1100	1200
$RMSE$	0.0041	0.0031	0.0023	0.0017	0.0012	0.0006	0.0003	6.9897×10^{-5}	5.6801×10^{-6}

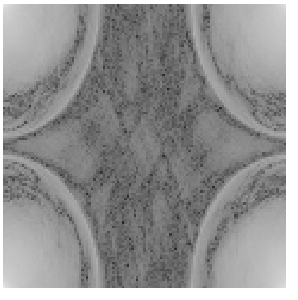

Figure 8. Denoising result with adaptive bandpass filtering.

Table 6. RMSE values for adaptive bandpass filtering.

cutoff	290	300	310	320	330	340	350	360	370
$RMSE$	2.3133	1.6633	1.1416	0.7205	0.3921	0.1888	0.0538	0.0011	0

The non-local means filtering method has three parameters, all of which have a certain effect on the denoising effect: the similarity window radius f, the search window size t, and the filtering parameter h. The size of the search window determines the computational complexity; the larger the window, the longer the computation time. The filtering parameter h plays a decisive role in the denoising effect. Therefore, for the non-local means filtering method, it is necessary to consider these parameters comprehensively. In this study, only the parameter h is considered, while keeping other parameters constant. After individual analysis, it is found that when $f = 6$, the $RMSE$ is minimized. As t increases, the $RMSE$ also increases, but the computation time also becomes longer. Therefore, $t = 5$ can be chosen to balance effectiveness and computation time. The denoising results and $RMSE$ values under these conditions are shown in **Figure 9** and **Table 7**. It can be observed that when $h = 0.001$, $f = 6$, and $t = 5$, the $RMSE$ is minimized.

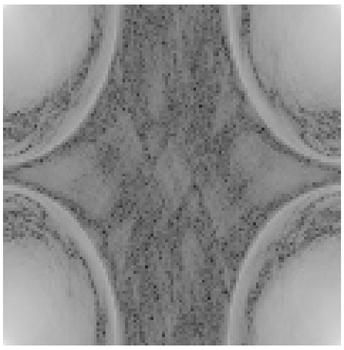

Figure 9. Denoising result with non-local means filtering.

Table 7. RMSE values for non-local means filtering.

h	0.001	0.101	0.201	0.301	0.401	0.501	0.601	0.701	0.801
RMSE	0	0.0035	0.0050	0.0061	0.0075	0.0085	0.0096	0.0147	0.0162

Figure 10 and **Table 8** present the results and RMSE values of the regularization filtering method. It can be observed from the figure that when lambda = 0.1, the *RMSE* is minimized, indicating the best denoising effect under this condition.

In conclusion, the denoising results of blind noise removal provided in this study exhibit similarities. The assessment of denoising effectiveness relies solely on the quantified *RMSE* values. Based on the obtained results, it can be concluded that Gaussian filtering, median filtering, mean filtering, adaptive bandpass filtering, and non-local mean filtering methods proposed in this paper all exhibit excellent performance in addressing blind noise issues. Conversely, wavelet filtering, bilateral filtering, and regularization denoising methods exhibit less effective results in handling the dataset compared to the former methods.

From the analysis above, it can be inferred that the proposed method demonstrates favorable outcomes in denoising and restoring blind noise images. Moreover, utilizing *RMSE* as the standard for evaluating image restoration proves to be rational. It is noteworthy that the selection of different methods and parameters significantly influences the effectiveness of image restoration.

From **Tables 1-8**, it is evident that variations in parameters within the same method lead to changes in *RMSE* values, indicating different levels of image restoration effectiveness. Therefore, it is essential to select appropriate parameters to achieve optimal denoising results. The proposed method in this paper can adaptively choose the best parameters. By analyzing the *RMSE* values of each method and plotting them in **Figure 11**, it can be observed that the parameters vary from 1 to 9 for wavelet filtering, median filtering, and mean filtering, while they range from 0.1 to 0.9 for Gaussian filtering and regularization filtering. And the parameters for other methods follow a regular pattern. Upon examination of **Figure 11**, it is noticeable that wavelet filtering and Gaussian filtering exhibit smoother changes in *RMSE* values compared to the comparative group, and they

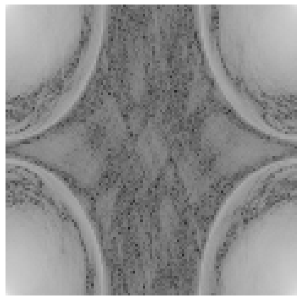

Figure 10. Denoising result with regularization filtering.

Table 8. RMSE values for regularization filtering.

lambda	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
RMSE	0.0314	0.0793	0.1270	0.1718	0.2133	0.2515	0.2869	0.3196	0.3501

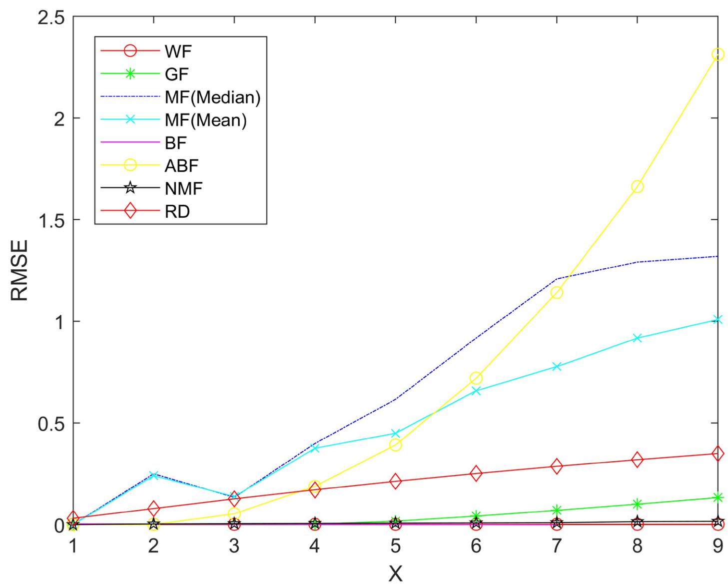

Figure 11. Comparison of *RMSE* values for each method.

also yield smaller *RMSE* values. This indicates that wavelet filtering and Gaussian filtering have advantages in handling experimental noise compared to other methods in the comparative group. Furthermore, it suggests that different methods have varying effects on noise processing, which is one of the factors influencing image restoration.

It is shown through experiments that the method proposed in this paper has good denoising effect for blind noise sources. And it can be found through comparison that there are differences between different methods. The effect is not the same for different noise processing. However, the method also has limitations. Recording the experimental time shows that the computation time of the method is a multiple order of a single method. Therefore, there is still room for improvement of the method. The possibility of reducing the computation time can be further explored.

4. Conclusion

To address the challenge of denoising and restoring images corrupted by blind noise or unknown mixed noise, this paper proposes a method for image processing based on RMSE and multiple adaptive filtering techniques. By selecting appropriate parameter ranges and applying denoising processing to the noisy spectrum, the method computes RMSE to determine the best denoising outcome. The smaller the RMSE, the better the denoising effect. Finally, the results of all methods are comprehensively compared to select the optimal denoising outcome which has the minimal RMSE values. In this experiment, the non-local means filtering, adaptive bandpass filtering, median filtering, median filtering and Gaussian filtering have the least RMSE, indicating they have the best denoising effect. Experimental results demonstrate that the proposed method effectively removes noise and yields satisfactory performance.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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