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An Effective Denoising Method for Images Contaminated with Mixed Noise Based on Adaptive Median Filtering and Wavelet Threshold Denoising

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Abstract

Images are unavoidably contaminated with different types of noise during the processes of image acquisition and transmission. The main forms of noise are impulse noise (is also called salt and pepper noise) and Gaussian noise. In this paper, an effective method of removing mixed noise from images is proposed. In general, different types of denoising methods are designed for different types of noise; for example, the median filter displays good performance in removing impulse noise, and the wavelet denoising algorithm displays good performance in removing Gaussian noise. However, images are affected by more than one type of noise in many cases. To reduce both impulse noise and Gaussian noise, this paper proposes a denoising method that combines adaptive median filtering (AMF) based on impulse noise detection with the wavelet threshold denoising method based on a Gaussian mixture model (GMM). The simulation results show that the proposed method achieves much better denoising performance than the median filter or the wavelet denoising method for images contaminated with mixed noise.

Keywords

Adaptive Median Filter (AMF), Gaussian Mixture Model (GMM), Image Denoising, Mixed Noise, Wavelet Threshold Denoising

1. Introduction

Natural images are typically affected by more than one type of noise. The quality of images contaminated with mixed noise is seriously degraded. Moreover, mixed noise is more difficult to remove thoroughly than noise of individual types. In recent years, various types of filtering methods and improved algorithms have been proposed to remove different types of noise, including median filtering, the wavelet threshold method [1,2], and adaptive median filtering (AMF) [3]. These methods achieve different levels of performance for different types of noise. However, effective filtering cannot be performed if only one type of denoising method is used to remove all of the mixed noise from an image. To solve this problem, many improved mixture denoising methods have been proposed in recent years.

In [4], the authors proposed an effective wavelet-domain iterative center weighted median filter

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(ICWMF) for image denoising. By using the inner-scale and inter-scale dependencies of wavelet coefficients, an improved estimation of the variance field is acquired using the proposed filter. The experimental results show that this filter can both smooth the noisy variances of the wavelet coefficients and preserve the edge information contained in the large-magnitude wavelet coefficients. Li et al. [5] proposed a new mixture filter method that can remove symmetrical noise and Gaussian noise. In this method, the pixels are first divided into two classes, which include pixels contaminated with symmetrical noise and pixels contaminated with Gaussian noise. The average filter or median filter is then adopted to remove the noise according to the classification. The simulation results demonstrate that the method achieves a certain denoising effect. However, the denoising effect is far from the expected results. To remove additive impulse noise or white Gaussian noise, a new denoising method based on the median filter and wavelet theory was proposed by Ma and Li [6]. Canny edge detection was first used in this paper to obtain the basic outlines from noisy images. An improved adaptive median filter was used to remove salt noise, and a Coiflet wavelet system was adopted to remove pepper noise. It is well known that the median filter does not display good performance with Gaussian noise, whereas the wavelet transform can effectively remove Gaussian noise. Based on this, Dong and Wang [7] proposed an image denoising method that combines a biorthogonal wavelet transform and a median filter. The experimental results indicate that this method achieves good denoising effects, and the details of images are well preserved. To remove homogeneous impulse noise, Sree et al. [8] proposed a novel adaptive median-based lifting filter for image denoising. In their method, the noise is removed by lifting the scheme of the second-generation wavelets with the adaptive median-based lifting filter. The results attest to the efficiency of the proposed method. Wu [9] proposed a denoising algorithm that operates in the wavelet domain and employs multistage median filtering. This method determines the smoothing or edge regions in the wavelet domain by using the difference between the maximum value and the minimum value of the medians in the four directions of the filtering window. In this way, the wavelet coefficients of the noise can be well suppressed. Experimental results show that this method displays a greater ability to separate signals from noise than the threshold denoising method. In [10], the authors presented a joint wavelet transform scheme that employs iterative noise density and median filtering to remove impulse noise from digital images. The wavelet coefficients with slight increases in noise density are derived first. These coefficients are then modified further by a median filter. Simulation results show that this method displays extraordinary improvement over the Gaussian noise model. In addition, it removes most of the noise, and the denoised images have better image quality. In [11], the authors introduced four different filter methods, including the discrete wavelet transform (DWT) denoising method, the median filter, the Wiener filter, and the bilateral filter. In addition, they compared these denoising methods and a special filter that is a combination of these filters. The experimental results show that the use of the special filter results in clearer and visually better image quality; this filter can recover many more details of the original images. In [12], a diffusion scheme that employs a mean filter and wavelet coefficient magnitude was proposed by the authors and was introduced into image denoising schemes. It is generally known that the shrinkage function plays an important role in the performance of wavelet-based image denoising methods. To obtain a better shrinkage function, the local mean filter is used to effectively extract noiseless wavelet coefficients, whereas the original noisy wavelet coefficient magnitudes are used to offset the negative effects generated by information extraction. The experimental results show that this method achieves better performance than the existing wavelet-based denoising methods. Zhang and Wang [13] proposed a switching median-mean filter for the removal of high-density impulse noise from digital images. In their method, pixels that are labeled noiseless in the detection process remain untouched, and noisy pixels are replaced by the reference image based on a switching mean-median filter with a 3×3 window. Experimental results show that the proposed filter outperforms some existing methods according to both visual and quantitative indexes. In addition, this algorithm is efficient in removing high-density impulse noise and preserves the details of images well. To suppress impulse noise, Faragallah and Ibrahem [14] proposed an adaptive switching weighted median filter (ASWMF). This filter includes two processes, a noise detection process and a noise removal process. In the noise detection process, a pixel is classified as either a "noiseless pixel" or a "noisy pixel" by checking the noise candidate against the local mean value. The noisy pixels are then substituted by their weighted median values obtained using ASWMF within window sizes of 3×3 or 5×5. Simulation results indicate that this method achieves outstanding performance in removing impulse noise. Although these methods achieve good performance in image denoising, there are still many problems that must be solved, such as image blurring and high computational complexity.

In this paper, a new mixture filter method is proposed for mixed noise composed by Gaussian noise and impulse noise. In this method, the median filter and wavelet denoising algorithm are combined to remove the mixed noise. The corrupted image is first filtered by adaptive median filter based on impulse noise detection. Due to its good property on impulse noise removal, the impulse noise in the noisy image could be removed at a large extent. After that, a threshold process is applied to the wavelet coefficients to remove the Gaussian noise in the wavelet domain, and then we get the noiseless wavelet coefficients. After image reconstruction, the denoised image is obtained at last.

The rest of this paper is organized as follows. Section 2 introduces the theories of median filter denoising and wavelet threshold denoising, respectively, and gives the comparisons of these two denoising methods. Section 3 introduces the proposed method. Experimental results and performance analysis are presented in Section 4. Conclusions and future work are given finally in Section 5.

2. Related Work

2.1 Median Filter Denoising

The median filter denoising algorithm was first proposed by Tukey [15]. The theory of this algorithm is as follows. First, an adjacent area around a center pixel is determined; this area is typically square. Second, the grayscale values of the pixels are sorted, and the median is regarded as the new value of the center pixel. Due to its favorable properties, the median filter algorithm can smooth images and remove noise to some degree. The noise can be removed because the median filter is sensitive to the values that differ strongly from the mean value in the neighborhood. In the median filter, each point value of a digital image block or a digital sequence is replaced by the median in its neighborhood.

The median filter denoising method has been widely used, due to its simplicity and good effectiveness in removing low-intensity noise. However, the median filter denoising algorithm cannot effectively remove high-intensity noise. Images contaminated with high-intensity noise may be seriously damaged after filtering, which produces sharp edges and image distortion. Moreover, the conventional median filter employs a fixed, predefined window to filter out noise. Because the noise intensity differs among regions, this method is impractical in practical applications. To improve the filtering effect of the median filter, many improved methods have been proposed. One of the improved median filters is the adaptive median filter [16]. As the name suggests, an adaptive median filter can change the size of the filter window, depending on whether the value of the window median represents noise. If the pixel in the center of the filter window is contaminated with noise, the median is calculated as the substitute for the pixel. If the pixel of the filter window center is not a noise point, its current value remains unchanged. An adaptive median filter can filter out impulse noise with a relatively high noise ratio. Meanwhile, it maintains image details very well.

2.2 Wavelet Threshold Denoising

The wavelet threshold denoising method, which was first proposed by Donoho and Johnstone [17], has been widely applied, due to its ease of calculation and good filtering effectiveness. The key steps involved in the wavelet threshold denoising method are processing the decomposed wavelet coefficients and obtaining the estimated wavelet coefficients. The wavelet threshold denoising method is a simple and effective denoising algorithm. The principle of this method is described as follows. In general, the energy of an image with relatively large wavelet coefficients is mainly distributed at high frequencies. Noise energy, which has relatively small wavelet coefficients, is spread all over the coefficients. Given these traits, a threshold can be set to remove the noise while preserving the wavelet coefficients of the original image. The wavelet coefficients that exceed the threshold are regarded as the image component. In contrast, the wavelet coefficients with values that are much smaller than the threshold are regarded as noise that should be removed.

The wavelet threshold denoising method has two important factors that significantly affect its filtering performance. One is the threshold, and the other is the selection of the threshold function [18]. For the selection of threshold functions, soft threshold functions and hard threshold functions are generally used. To estimate the threshold, the VisuShrink, minimax, and BayesShrink thresholds are often used. In general, the wavelet threshold denoising method, which is based on the Gaussian mixture model (GMM), displays the best filtering performance among these methods.

2.3 Comparisons of Single Filter Denoising

The analysis presented above shows that the AMF algorithm based on impulse detection displays the greatest denoising effectiveness among the median filtering algorithms, whereas the wavelet threshold denoising algorithm based on the GMM displays the best denoising effectiveness among the wavelet threshold denoising algorithms. Therefore, these two types of filtering algorithms are selected to represent the median filtering methods and wavelet denoising algorithms. To compare their filtering performance, we display denoised versions of images with impulse noise, Gaussian noise, and mixed noise.

Fig. 1 shows Lena images filtered by the improved AMF and wavelet denoising algorithm when the intensity of impulse noise is 0.2. As we can see, the improved median filter displays greater effectiveness in removing impulse noise. The filtering performance of the wavelet denoising method based on GMM is far from ideal for impulse noise. The image to which the wavelet denoising method based on GMM has been applied is rather blurry and displays serious distortion. Fig. 2 shows the Lena image filtered by the improved AMF and wavelet denoising algorithm for Gaussian noise with an intensity of (0, 0.01). It can be observed from Fig. 2 that the GMM algorithm achieves a better filtering effect for Gaussian noise. The image filtered by the denoising method based on the GMM algorithm displays less distortion than the improved median filtering algorithm. In other words, the improved median filtering algorithm is not appropriate for removing Gaussian noise.

Fig. 1. Effectiveness of denoising the Lena image contaminated with impulse noise: (a) original image, (b) noisy image, (c) improved AMF, and (d) GMM algorithm.

To test the denoising performance of these two methods for mixed noise, Fig. 3 shows the Lena image contaminated with mixed noise and the denoising results obtained with the improved median filter and the GMM algorithm. The image is first contaminated with impulse noise with an intensity of 0.2 and Gaussian noise with an intensity of (0, 0.01). We then apply the improved adaptive median filter and wavelet denoising algorithm separately to remove the mixed noise. Fig. 3(c) and 3(d) show that these two algorithms do not display good effectiveness in denoising images containing mixed noise. The post-filtering image quality is seriously degraded.

Fig. 2. Effectiveness of denoising the Lena image contaminated with Gaussian noise: (a) original image, (b) noisy image, (c) improved AMF, and (d) GMM algorithm.

3. The Proposed Method

The above analysis shows that mixed noise is more difficult to remove than noise of individual types. In addition, the filtering performance of any single filter is barely satisfactory for mixed noise. Thus, combinations of different filtering methods are needed to remove mixed noise. Many different methods to remove mixed noise from images have been proposed. In this paper, an improved method of removing mixed noise is proposed that is based on [5]. In this method, the median filter and wavelet denoising algorithm are combined to remove mixed noise.

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

Fig. 3. Effectiveness of denoising the Lena image contaminated with mixed noise: (a) original image, (b) noisy image, (c) improved AMF, and (d) GMM algorithm.

Based on a statistical analysis of the characteristics of noise in the wavelet transform, it can be seen that impulse noise has relatively large coefficients in the wavelet domain. If we apply a thresholding process in the wavelet domain, a larger threshold must be chosen. However, the wavelet coefficients of the edge details in images are often relatively small. Therefore, if we were to adopt a larger threshold, the wavelet coefficients of the detailed information would be removed when the wavelet coefficients are reduced using the threshold of impulse noise. We can infer that, after filtering, the image would be quite blurry. To address this issue, we filter the impulse noise first and subsequently filter the Gaussian noise by the method of threshold quantization in the wavelet domain. The median filter method based on impulse detection is very effective in filtering impulse noise. To remove mixed noise from images, a novel image denoising method based on median filtering and the wavelet transform is proposed in this paper. A block diagram of the proposed method is shown in Fig. 4, and the specific steps are as follows.

First, a noisy image is filtered using a median filter based on impulse noise detection. Due to the good performance of this method in removing impulse noise, the impulse noise in the noisy image should be filtered out to a large extent. Second, the image after median filtering is decomposed using a two-dimensional wavelet transform. A thresholding process is applied to the wavelet coefficients in the wavelet domain. By wavelet denoising, we obtain noiseless wavelet coefficients. After wavelet reconstruction, we finally obtain the denoised image.

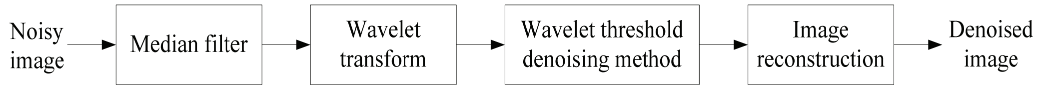

Fig. 4. Block diagram of the proposed denoising method.

4. Experimental Results and Analysis

To test the filtering performance of the proposed method, the Lena image and the Barbara image are adopted as test subjects. Because the Lena image has greater areas of smooth regions, whereas the Barbara image includes more textural details, these two images serve as representative images to test the filtering performance of the proposed method. To permit an improved comparison, the sizes of the Lena and Barbara images are both 512×512. White Gaussian noise and impulse noise with different intensities are initially added to these two images. In other words, the images are severely contaminated with mixed noise. Various filtering methods are then adopted to remove the mixed noise. In the experiment, we compare the filtering performance of the proposed method with the AMF algorithm based on impulse noise detection and the wavelet denoising algorithm based on GMM.

Table 1. PSNR values of the Lena image filtered using various filtering algorithms at different intensities of mixed noise (unit: dB)

Gaussian/impulse noise intensities	Noisy image	Improved AMF	GMM algorithm	Proposed method
(0, 0.01) / 0.1	14.29	20.56	22.07	28.91
(0, 0.01) / 0.2	11.87	20.94	22.53	28.66
(0, 0.01) / 0.3	10.31	21.19	21.51	28.19
(0, 0.02) / 0.1	13.41	17.88	24.12	26.97
(0, 0.02) / 0.2	11.42	18.26	22.96	26.82
(0, 0.02) / 0.3	10.01	18.64	21.30	26.48

Table 2. PSNR values of the Barbara image filtered using various filtering algorithms at different intensities of mixed noise (unit: dB)

Gaussian/impulse noise intensities	Noisy image	Improved AMF	GMM algorithm	Proposed method
(0, 0.01) / 0.1	14.17	20.50	20.40	25.46
(0, 0.01) / 0.2	11.56	20.65	20.25	25.06
(0, 0.01) / 0.3	10.19	20.71	19.54	24.60
(0, 0.02) / 0.1	13.34	17.90	21.44	23.65
(0, 0.02) / 0.2	11.27	18.17	20.49	23.43
(0, 0.02) / 0.3	9.89	18.45	19.48	23.22

The peak signal-to-noise ratio (PSNR) [8] is adopted in this paper to evaluate the quality of the denoised images. Tables 1 and 2 show the PSNR values in dB of the Lena image and the Barbara image after denoising using various algorithms. From Table 1, we can see that, compared with the AMF algorithm based on impulse noise detection and the wavelet denoising algorithm based on GMM, the proposed method has higher PSNR values at all noise levels. The PSNR values of the proposed method reflect improvements of at least 4 dB compared to the other two methods, thus demonstrating the effectiveness of the proposed method in removing mixed noise. Similar conclusions can be drawn from Table 2.

To evaluate the subjective characteristics of the denoised images, different combinations of Gaussian noise and impulse noise with different intensities are added to the Lena image and the Barbara image. In this experiment, we add Gaussian noise with a noise intensity of (0, 0.01) and impulse noise with a noise intensity of 0.01 to the images. Figs. 5 and 6 show the filtering performance of these methods for the Lena and Barbara images, respectively. By comparing these figures, we can see that the proposed method achieves better performance than the AMF algorithm based on impulse noise detection and the wavelet denoising algorithm based on GMM. The noise in the images is effectively reduced. In addition, the denoised images obtained using the proposed method display less distortion, and the quality of the denoised images is significantly improved. It is unavoidable that the images become blurred after filtering, but the results of filtering are still acceptable to the human eye.

Based on the above evaluations, we can draw the following conclusions. Though the improved adaptive median filter can effectively remove Gaussian noise, the images are blurred after filtering. The wavelet denoising method based on GMM cannot completely remove impulse noise from images. In contrast, the proposed method, which combines the median filter with the wavelet denoising algorithm, achieves better filtering performance than the single denoising filter mentioned above. In addition, the denoising effect of the proposed method is more complete; thus, Gaussian noise and impulse noise can be filtered out effectively. This method retains the details and edge information contained in images well. Similar results are obtained for other standard test images.

5. Conclusion and Future Work

To remove mixed noise composed of Gaussian noise and impulse noise, a new mixture filtering method is proposed in this paper. In this method, a corrupted image is first filtered by AMF based on impulse noise detection. The wavelet transform is subsequently applied to the image filtered by AMF, and a thresholding process is applied to the wavelet coefficients of the image in the wavelet domain. In this way, we obtain noiseless wavelet coefficients. Finally, we obtain the restored image after image reconstruction. The experimental results show that the proposed denoising method achieves greater filtering effectiveness than the AMF and wavelet threshold denoising methods when these methods are used independently to remove mixed noise. In addition, the images after filtering have a better visual appearance. In future work, we plan to further improve the denoising ability and reduce the computational complexity of this method.

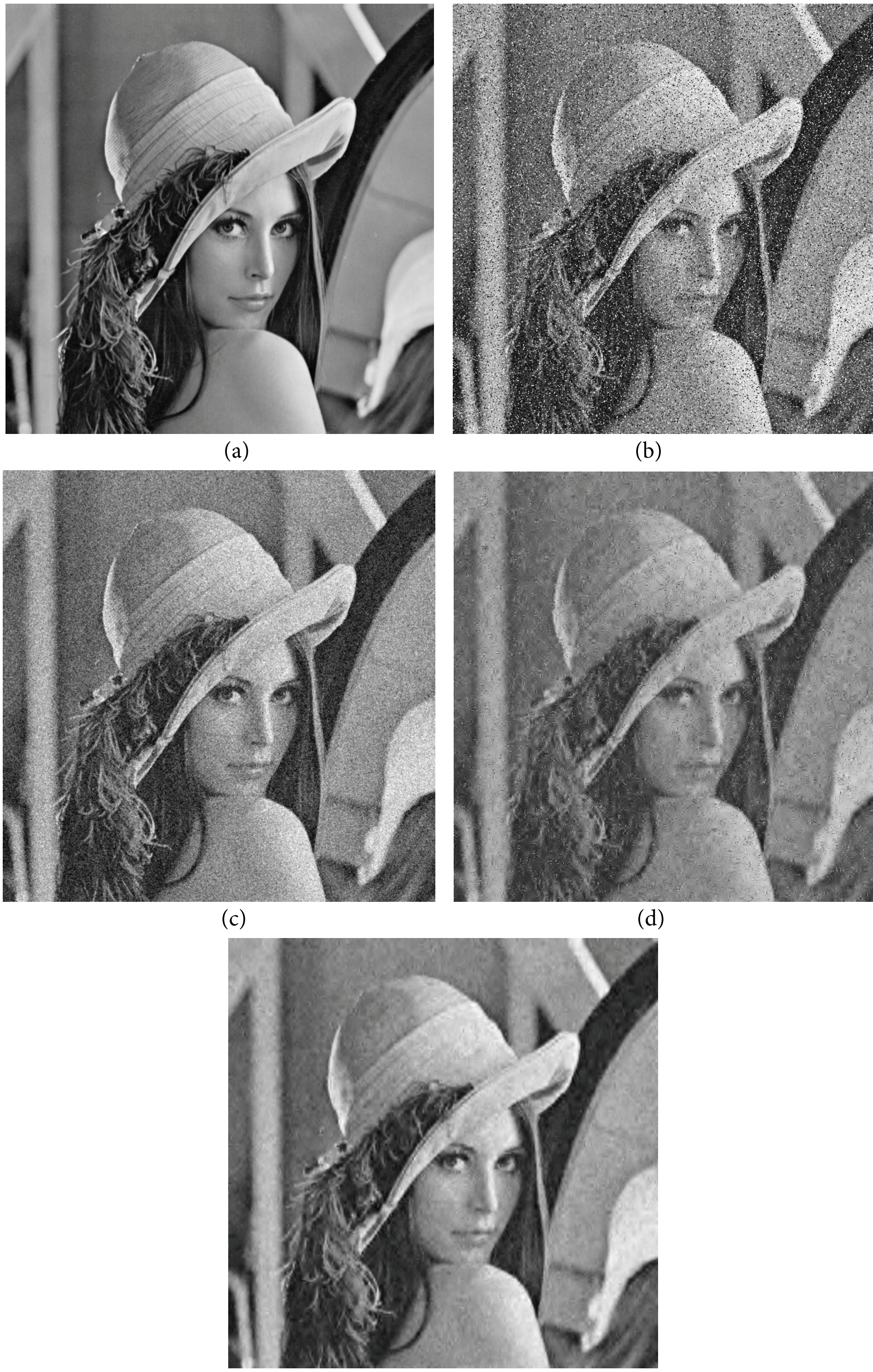

Fig. 5. Denoised Lena image with mixed noise: (a) original image, (b) noisy image, (c) improved AMF, (d) GMM algorithm, and (e) the proposed method.

(a)

(b)

(c)

(d)

(e)

Fig. 6. Denoised Barbara image with mixed noise: (a) original image, (b) noisy image, (c) improved AMF, (d) GMM algorithm, and (e) the proposed method.

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