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Result Analysis of Blur and Noise on Image Denoising based on PDE

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Abstract

The effect of noise on image is still a challenging problem for researchers. Image Denoising has remained a fundamental problem in the field of image processing. Wavelets give a superior performance in image denoising due to properties such as sparsity and multi resolution structure. Many of the previous research use the basic noise reduction through image blurring. Blurring can be done locally, as in the Gaussian smoothing model or in anisotropic filtering; by calculus of variations; or in the frequency domain, such as Weiner filters. In this paper we proposed an image denoising method using partial differential equation. In our proposed approach we proposed three different approaches first is for blur, second is for noise and finally for blur and noise. These approaches are compared by Average absolute difference, signal to noise ratio (SNR), peak signal to noise ratio (PSNR), Image Fidelity and Mean square error. So we can achieve better result on different scenario. We also compare our result on the basis of the above five parameters and the result is better in comparison to the traditional technique.

Keywords

Image denoising, PDE, SNR, PSNR, Weiner Filter

1. Introduction

Denoising of image data has been an active area of research, with several different approaches being proposed using techniques such as wavelets, isotropic and anisotropic diffusion, bilateral filtering, etc. We observe that image contains a large amount of redundancy in plain areas where adjacent picture element have almost the same values which means the pixel values are highly correlated [1][2]. In addition, image can contain subjective redundancy, which is determined by properties of a human visual system (HVS). However, HVS present some tolerance to distortion that depending on image contents and viewing condition [2]. Discrete wavelet transform (DWT) offers adaptive spatial-frequency resolution (better spatial resolution at high frequencies and better frequency resolution at low frequencies) that is well suited to the properties of an HVS (Human Visual System) [2]. However, it requires mathematical functions thus; the coding scheme is more complex and not applicable in real-time situation.

All algorithms in the research area of Image denoising is playing an important role in image processing systems. Images mixed with noise are harmful to the progress of image processing. So image denoising is the foundation of other aspects of image processing. There are several algorithms had been proposed recently, such as algorithms based on wavelet transform [3] [4] [5], algorithm based on spatial filters [6] and algorithm based on fuzzy theory [7]. In [8] and [9] the authors used the method of least squares support vector machines and image decomposition respectively. Later, some researchers proposed an algorithm using non-aliasing contoured transform [10] and partial differential equation [11].

We provide here an overview of Image Compression Technique. The rest of this paper is arranged as follows: Section 2 introduces Image denoising; Section 3 describes about Recent Scenario; section 4 shows the proposed approach. Section 5 shows the result analysis; Section 6 describes Conclusion.

2. Image Denoising

Image Denoising play an important role in Image processing task. The main task of Image denoising is to remove noise when the edges are preserving. Noise is a common problem in the image processing task. If we consider the very high and accurate resolution image then also there is the chance of noise. The main purpose or the aim of image denoising is to recover the main image from the noisy image.

$$V(i)=U(i) + N(i)$$

Where v(i)is the observed value, u(i)is the "true" value and n(i) is the noise perturbation at a pixel i. There are lot of way to model the noise. The basic procedure for model the effect of noise on a digital image is to add a Gaussian white noise. In other words we can say that to use a Gaussian filter with the noisy image as input-data to the PDE-model. For some purposes this kind of denoising is adequate. The main advantage of the above approach is the better speed and the major drawbacks of the above models are loose ability for preserving edges. In the other hand can handle edges in a much better way than linear models can. Here we produce an example for better understanding. In figure 1 we show the simple image example. How it is affected with noise and blur parameters is shown in Figure 3 and figure 4.

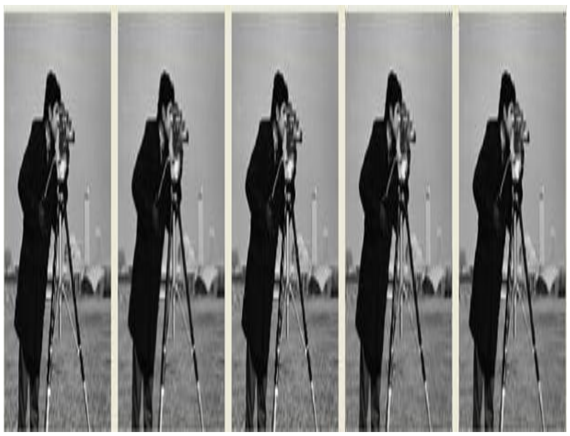

Figure 1: Image 1

If we clearly investigate the performance of subparts, then we observe how the image is affected by Noise and Blur which degrades the performance of the image. In many research areas related, such as target detecting and tracking, edge detecting and image registration, image denoising is the first step of process and the effect is very generous in the subpart.

Figure 2: Subpart of Image 1

Figure 3: Subpart of Image 1 with Noise

Figure 4: Subpart of Image 1 with Noise and blur

The three images above show a small excerpt of the normal vectors of the above shown image. The first image subpart shows the normal of the original image, the middle image shows the normal of the noisy image, and the last image shows the smoothed normal.

3. Literature Review

In 2009, Tongzhou Zhao et al. [12] presented a new approach by using discrete multi-wavelet transform to remote sensing image denoising. The wavelet theories have given rise to the wavelet thresholding method, for extracting a signal from noisy data. According to the authors Multi-wavelets can offer simultaneous orthogonality, symmetry and short support, and these properties make multi-wavelets more suitable for various image processing applications, especially denoising. Denoising of images via thresholding of the multiwavelet coefficients result from pre-processing and the multi-wavelet transform can be carried out by treating the output by the authors. They observe that the Multiwavelet transform technique has a big advantage over the other techniques that it less distorts spectral characteristics of the image denoising. Their experimental results show that multi-wavelet on image denoising schemes outperform wavelet-based method both in subjectively and objectively.

In 2009, Carlos A. Júnez-Ferreira et al. [13] observe that the denoising is an important task inside the image processing area. In order to overcome this challenging problem, diverse proposals have been done, like Non-Local means (NL-means) algorithm. Authors present a fast algorithm that uses a preliminary segmentation combined with NL-means for image denoising. Firstly, the algorithm performs a subsampling, called Preliminary Segmentation-Based Subsampling (PSB Subsampling) while reducing the data quantity to be processed, based in the preliminary segmentation information given by the noisy image. This preliminary segmentation finds out an image partition where regions are labeled as significant or non-significant. In a second step, the denoising procedure is done, but NL-means is applied only on some pixels, reducing the data quantity again. The selection of these pixels is done based on information contributed by a segmentation of the subsampled image. According to the authors experimental results show that the implementation of this proposal is quite faster than existing bibliography and it could be used in other image processing tasks like segmentation.

In 2010, Yan He et al. [14] presents a novel image denoising method based on non-aliasing Contour let transform(NACT) according to coefficient inter-scale correlation. A noisy image was decomposed into a low frequency approximation sub-image and a series of high frequency detail sub-images at different scale and direction via NACT. In the transform domain, the inter-scale correlation of the signal coefficients was strong, and there was weak inter-scale correlation for noise coefficients, so the noise in the high frequency detail sub-images was removed by using of non-Gaussian bivariate model .According to the authors the result has higher operational efficiency, and it can overcome the aliasing in Contour let transform and avoid “scratching” phenomenon in the reconstructed image.

In 2010, Xiaotian Wang et al. [15] propose a translation invariant directional lifting (TI-DL) by employing the cycle-spinning based technique to reduce artifacts in denoising results. Moreover, the inefficiency and high computational complexity of the orientation estimation technique in ADL strongly influences the performance. In order to achieve better denoising results, they adopt 2-D Gabor filters for orientation estimation to achieve better orientation estimation results with lower complexity. Experimental results demonstrate that the proposed method achieves state-of-art denoising performance in terms of both objective (PSNR) and subjective (SSIM) evaluation.

In 2010, Guodong Wang et al. [16] propose a denoising method based on adaptive sparse representation in order to avoid estimating the noise variance and remove the white Gaussian noise. It trains the initialized dictionary based on training samples constructed from noised image. The training process is finished by an iteration algorithm which alternates between adaptive sparse representation and dictionary update. Based on the trained dictionary, noise reduction is conducted through adaptive sparse representation of the noised image. Compared with adaptive Wiener filtering and adaptive denoising based on Basis Pursuit, the proposed method could remain more image details and have better performance. With the proposed method, laser electronic speckle interference image could be enhanced and its interference fringe became clearer.

In 2011, Harnani Hassan et al. [17] investigated on suitability wavelet thresholding and translation invariant methods of image denoising to remove noise using orthogonal wavelet basis. The performance of the image denoising is shown in terms of PSNR and visual performance. The result shown translation invariant gave better PSNR and visual performance than wavelet transform method.

In 2011, Chengdong Wu et al. [18] proposed a novel pavement image denoising method based on shearIet transform. Because that the pavement crack has continuous liner geometrical feature which can be captured by shearlets very efficiently with more directions than wavelets, the pavement image denoising method based on the shearlet transform can obtain a great improvement than traditional method. Background fitting is used to deal with the low frequency component of the image, which can banlance the energy distribution of the pavement image. Then coarse scale coefficients of shearlet are selected under multiple thresholds. The coefficients obtained by low threshold is used for reconstruction of the main parts of cracks, and the coefficients obtained by high threshold is employed to extract crack position and direction information, which is fused with the threshold at fine scale to distinguish the noise and fine parts of cracks. The experimental results show that this method can smooth the most of noisy spots but keep the cracks details well and have less pseudo-Gibbs artifacts.

In 2011, Dongni Zhang et al. [19] proposed an aggregation function to improve the performance of the conventional denoising method based on low rank matrix completion. Since this method determines the denoised value of each pixel by averaging the corresponding pixels in the denoised image patches, the performance can be improved by a reasonable aggregation function. Their proposed aggregation function exploits the intensity similarity and geometry closeness of the denoised patches, to reduce the unwanted artifacts in the synthesized denoised image. Their Experimental results show that the proposed method achieves substantial PSNR improvement as compared with the conventional denoising algorithm.

In 2012, Abdolhossein Fathi et al. [20] proposes a statistically optimum adaptive wavelet packet (WP) thresholding function for image denoising based on the generalized Gaussian distribution. It applies computationally efficient multilevel WP decomposition to noisy images to obtain the best tree or optimal wavelet basis, utilizing Shannon entropy. It selects an adaptive threshold value which is level and subband dependent based on analyzing the statistical parameters of subband coefficients. In the utilized thresholding function, which is based on a maximum a posteriori estimate, the modified version of dominant coefficients was estimated by optimal linear interpolation between each coefficient and the mean value of the corresponding subband. Their Experimental results, on several test images under different noise intensity conditions, show that the proposed algorithm, called OLI-Shrink, yields better peak signal noise ratio and superior visual image quality measured by universal image quality index compared to standard denoising methods, especially in the presence of high noise intensity.

In 2012, Kehua Su et al. [21] introduce a sparse and redundant representations algorithm based on over complete learned dictionary to process different types of images. They use the K-SVD denoising framework and modify its initial dictionary, and then mainly focus on using it to study its denoising performance and suitability for different types of Images, and then compare it with some other image denoising algorithms. As to the remote sensing images denoising, the experiment results show that the K-SVD algorithm can leads to the state-of-art denoising performance at low noisy levels, but for high noisy levels, its performance isn't good on PSNR and visual effect, that is it cannot retain the local details of images.

In 2012, Guo-Duo Zhang et al. [22] proposes an image denoising method based on support vector regression; also this paper describes several other methods of image denoising. Simulation results show that the method can save the image detail better, restore the original image and remove noise.

In 2011, Jia Liu et al. [23] proposed an image denoising method using partial differential equation and bi-dimensional empirical mode decomposition. The bi-dimensional empirical mode decomposition transforms the image into intrinsic mode function and residue. Different components of the intrinsic mode functions present different frequency of the image. The different with the classic method of partial differential equation denoising is that we use partial differential equation of the intrinsic mode functions to filter noise. Finally, they reconstruct the image with the filtered intrinsic mode functions and residue.

4. Proposed Approach

If we think of an image then it is in the form double dimension array. The actual intensity is quantized between 0 to 255. Consider the example of figure 5. If we think about the below image it can be quantified in terms of array. The actual images are check with the variations in terms of intensity. In our approach our image is PDE denoised based on three different combinations.

Figure 5: Image

Our three parameters are noise effect, blur and blur with noise effect. If you want to see the difference between the noisy and non-noisy image which is shown in figure 6. It shows the distraction in the real image.

Figure 6: (left) image WITHOUT noise. (Right) image corrupted WITH noise

In the above picture the noise which is added is salt and pepper. If we change the noise type to Gaussian then the effect is different [Figure 7].

Figure 7: (left) image WITHOUT noise. (Right) image corrupted WITH noise

In the above picture the noise which is added is Gaussian. If we change the noise type to Speckle then the effect is different [Figure 8].

Figure 8: (left) image WITHOUT noise. (Right) image corrupted WITH noise

It means we have to adopt a methodology which is better in different noise parameter. In our proposed approach we consider different noise type including salt and pepper, Gaussian and Speckle. So that we can check the noise reduction in the better way.

The process of removing noise from an image is known as noise reduction or denoising. A standard denoising technique is the convolution of the image with a 2D Gaussian distribution. The formula is shown below:

$$G(x,Y)=1/\sqrt{2\pi\sigma^2}\quad \exp^{-(x2+y2)/2\sigma2}$$

In our approach we also use Average absolute difference, signal to noise ratio (SNR), peak signal to noise ratio (PSNR), image Fidelity and Mean square error for comparing the result. The mean difference is a measure of statistical dispersion equal to the average absolute difference of two independent values drawn from a probability distribution. A related statistic is the relative mean difference, which is the mean difference divided by the arithmetic mean. Signal-to-noise ratio (often abbreviated SNR or S/N) is a measure used in science and engineering that compares the level of a desired signal to the level of background noise. It is defined as the ratio of signal power to the noise power. A ratio higher than 1:1 indicates more signal than noise. The phrase peak Signal-to-Noise Ratio, often abbreviated PSNR, is an engineering term for the ratio between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation. Because many signals have a very wide dynamic range, PSNR is usually expressed in terms of the logarithmic decibel scale. The PSNR is most commonly used as a measure of quality of reconstruction of lossy compression codecs (e.g., for image compression).

All the parameters taken by us is calculated in the below manner:

First we find the absolute difference.

Step 1: absdiff = summation1/(mdsize(1)*mdsize(2));

Then we find the original mean:

Step 2: mean = mean(limg(:));
tmp = originalimg - mean_original;
sumsq = sum(tmp(:).^2);

Then we find the noise:

Step 3: noise = restoredimg - originalimg;
mean_noise = mean(noise(:));
tmp = noise - mean_noise;
summation = sum(tmp(:).^2);

Then we calculate the SNR value:

Step 4: snr = 10 * log10(sumsq /summation);
The process is quantizing for the level [0,255] and finds the multiplicative factor also, and then we calculate the PSNR which is shown below:

Step 5: V1 = tot * 255;
psnr = V1 /Total;
psnr = 10 * log10(psnr);

By this way we can calculate the difference between the original and the noisy image.

MSE is a risk function, corresponding to the expected value of the squared error loss or quadratic loss. MSE measures the average of the squares of the "errors." The error is the amount by which the value implied by the estimator differs from the quantity to be estimated.

We proposed an image denoising method using partial differential equation. In our proposed approach we proposed three different approaches first is for blur, second is for noise and finally for blur and noise. Because in our investigation one methodology is not sufficient to provide better result in all condition.

5. Result Analysis

In this section we explain our result. For this we taken five parameters Average absolute difference, signal to noise ratio (SNR),peak signal to noise ratio (PSNR), Image Fidelity and Mean square error as shown in table 1.

Table 1: Parameters for result Comparison

Parameters	Proposed (Blur)	Proposed (Noise)	Proposed (Blur + Noise)
Average absolute difference			
Signal to noise ratio (SNR)			
Peak signal to noise ratio (PSNR)			
Image Fidelity			
Mean Square Error			

Table 2: Parameter Values

Parameters	Values
Average Absolute difference	0
Signal to noise ratio (SNR)	High
Peak signal to noise ratio (PSNR)	High
Image Fidelity	0
Mean Square Error	0

The expected values or the ideal values are shown in table 2. On which we can compare our result.
We start the comparison taking consideration with blur as shown in figure 9 and the result is shown in table3. If we compare the result of table 3 with table 2, it shows good result.

Figure 9: Considering Blur Parameter

Table 3: Comparison Considering Blur Parameters

Parameters	Proposed (Blur)	Proposed (Noise)	Proposed (Blur + Noise)
Average absolute difference	0.000000	0.002409	0.000603
signal to noise ratio (SNR)	258	13.49	14.59
peak signal to noise ratio (PSNR)	294	49.79	50.90
Image Fidelity	0.000256	-0.044	-0.03
Mean square error	0.000000	0.002677	0.002071

Then we consider images with noise parameters as shown in figure 10 and the result is shown in table4.

If we compare the result of table 4 with table 2, it shows good result.

Figure 10: Considering Noise Parameter

Table 4: Comparison Considering Noise Parameters

Parameters	Proposed (Blur)	Proposed (Noise)	Proposed (Blur + Noise)
Average absolute difference	0.00697	0.0033	Null
Signal to noise ratio (SNR),	5.96	14.35	Null
Peak signal to noise ratio (PSNR)	42.26	50.66	Null
Image Fidelity	-0.25	-0.036	Null
Mean square error	0.0151	0.0022	

Then we consider images with noise and Blur parameters as shown in figure 11 and the result is shown in table5. If we compare the result of table 5 with table 2, it shows good result.

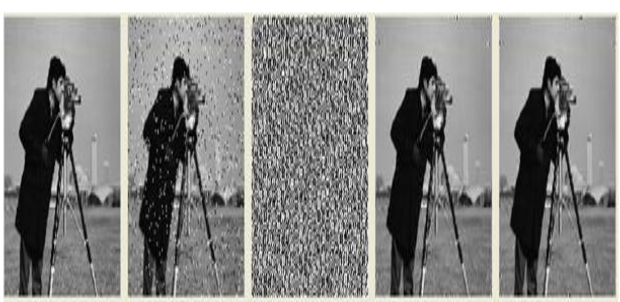

Figure 11: Considering Noise and Blur Parameters

Table 5: Considering Blur and Noise (Salt and Pepper) Parameters

Parameters	Proposed (Blur)	Proposed (Noise)	Proposed (Blur + Noise)
Average absolute difference	0.001413	0.002445	0.000638
signal to noise ratio (SNR),	-43.00	11.83	12.87
peak signal to noise ratio (PSNR)	-6.70	48.14	49.17
Image Fidelity	-19998	-0.06	-0.05
Mean square error	1193	0.0039	0.0030

After performing the above comparison we can show that the result is better in comparison to the traditional methods.

6. Conclusion

In this paper we have presented a method for image denoising. The process of removing noise from an image is known as noise reduction or denoising. A standard denoising technique is the convolutions of the image with a 2D Gaussian distribution. We apply sampling and convolution which is based on Weiner filters. We also provide comparison on the basis of five parameters Average absolute difference, signal to noise ratio (SNR), peak signal to noise ratio (PSNR), Image Fidelity and Mean square error. The result is better in comparison to the previous technique.

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