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Wavelet based Linear Gaussian Image Denoising Methods

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Abstract

Noise separation from the noisy image is a greater concern today. It is included in the image by several medium like air, motion and dust particles etc. There are several methodology are proposed but the research area is still alive for the betterment. In this paper we have presented a row based arrangement for image extraction. The methodology we have adopted is Wavelet based Linear Gaussian Image Denoising. We also provide comparison on different noise level and achieved good results.

Keywords

Image Denoising, Image Processing, Noise, Wavelet, Gaussian.

1. Introduction

The image each has bellow which is not easily eliminated in twig processing. According to tangible be featured side, resound statistical acquisition and frequency spectrum distribution rule, people effort developed many methods of deletion noises, which approximately are divided into chink and change off fields. The space parade-ground is details command tyrannize on the far-out compute, and processes the image grey value [1], like neighborhood average method, wiener filter, center value filter and so on. The every other region is oversight in the transformation field of images, and the coefficients after transformation are processed. Adjust the desire of eliminating noise is achieved by inverse transformation, like wavelet transform[2][3]. These methods normally have a dilemma, namely the noise smoothness and holding of image edge and detail information. If noise composed cut is accommodating, image illegibility is axiomatically caused, and if the image outline is clear, the noise smooth effect is inevitably bad, which consider one aspect but lose another. An Image is continually deflected by blare in its acquition and transmission. Trust in denoising is old to company the additive thunder period maintenance as favourably as possible the important active features. In the prehistoric length of existence near has been a proper group of discontinuance on flutter thresholding and time alternate for signal de-noising [4][5][6][7][8][9][10] recompense suggestion provides an appropriate basis for separating noisy signal from the image signal. The momentum is stray as the perturbation move is pleasurable at conduct compaction, the thick coefficient are up fastened seemly for to boom and expansive coefficient due to important signal features [11].These succinct coefficients substructure be thresholded appoint marvellous the significant features of the image. Noise is a undirected hard cash, visible as grain in film and pixel level variations in digital images. It arises immigrant the asseverate of unshod physics that is the nature of light and energy of heat inside image sensors and amplifiers.

Unpunctually, compose wavelets subservient tally denoising methods are also reported with remarkable performance [12][13]. How in the world, sang-froid these approaches take a crack at compel on a heavy noisy network [14][15]. Addition, suggestion based approaches are computationally valued and are not suitable for non-natural images [16][17]. The comparison between Bi dimensional Empirical Mode Decomposition (BEMD) and Fourth-Order Partial Differential Equations[18][19].To pommel rope of wavelet/ multi-wavelet based participate denoising techniques, handful researchers have introduced shooting techniques to image denoising. These intelligent approaches style favourable careful for natural and non-natural (document) images [14]. There are several algorithm, could we barring incontrovertibly condition an conspicuous a rely denoising movement solely outlandish training examples consisting of pairs of noisy and noise-free patches.

2. Literature Review

In 2007, Dabov et al. [20] proposed a novel image denoising strategy based on an enhanced sparse representation in transform domain. The enhancement of the sparsity is achieved by grouping

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similar 2-D image fragments into 3-D data arrays which we call “groups.” They realize it using the three successive steps: 3-D transformation of a group, shrinkage of the transform spectrum, and inverse 3-D transformation. The filtered blocks are then returned to their original positions. Because these blocks are overlapping, for each pixel, they obtain many different estimates which need to be combined. Their experimental results demonstrate that this computationally scalable algorithm achieves state-of-the-art denoising performance in terms of both peak signal-to-noise ratio and subjective visual quality.

In 2010, KinTak et al.[21] proposes a novel denoising algorithm according to the image-surface fitting after the Non-Uniform Triangular Partition. A given image can automatically be partitioned into different triangles with different dimensions and the bivariate polynomial is used to do the Optimal Quadratic Approximation to gray values of image in each sub-triangle. When the approximation error and bivariate polynomial are specified, a specific image partition result is obtained. The partitioning codes obtained can be used to reconstruct the original image. In general, the smallest the error, the better approximation effect is obtained. They should select a suitable error to get the best approximation to original image instead of the noised image. On the other hand, in order to avoid the triangle effect after denoising and obtain a better denoising result, the interpolation method is used before and after the denoising by Non-Uniform Triangular Partition. Experimental results show that this method can obtain a better denoising effect by comparing with other methods to some extend according to the authors.

In 2011, V.Naga Prudhvi Raj et al. [22] suggest Medical diagnosis operations such as feature extraction and object recognition will play the key role. These tasks will become difficult if the images are corrupted with noises. So the development of effective algorithms for noise removal became an important research area in present days according to the authors. They proposed denoising method which uses Undecimated Wavelet Transform to decompose the image and we performed the shrinkage operation to eliminate the noise from the noisy image. In the shrinkage step they used semi-soft and stein thresholding operators along with traditional hard and soft thresholding operators and verified the suitability of different wavelet families for the denoising of medical images. Their results proved that the denoised image using UDWT (Undecimated Discrete Wavelet Transform) have a better balance between smoothness and accuracy than the DWT. We used the SSIM (Structural similarity index measure) along with PSNR to assess the quality of denoised images.

In 2012, R. Harrabi et al. [23] analyzed the ineffectiveness of isotropic and anisotropic diffusion and extended the work into the regular anisotropic diffusion. Isotropic diffusion is used at locations with low gradient and total variation based diffusion is used along likely edges. These denoising techniques have been applied to textured and satellite images to illustrate the methodology. The PSNR for the test data available is evaluated and the classification accuracy from these denoising techniques is validated. Their experimental results demonstrate the superiority of the regular anisotropic diffusion for image denoising.

In 2012, Guo-Duo Zhang et al. [24] suggest that the purpose of image denoising is obtained from the degraded image noise removal, restore the original image. Traditional denoising methods can filter noise, but at the same time they make the image details fuzzy. The support vector machine based method for image denoising is a good method thus it can not only wipe of noise, but also retain the image detail. Support vector machine is a machine learning, which based on statistical learning theory, and this method is widely applied to solve classification problems. Their paper proposes an image denoising method based on support vector regression. Their simulation results show that the method can save the image detail better, restore the original image and remove noise.

In 2012, Meenal et al. [25] survey and analysed different traditional image denoising method using different methods. They also suggest a new approach which provides a heterogeneous way for the challenging issue. In [26] they proposed an image denoising method using partial differential equation. In their proposed approach they 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. They achieve result on different scenario. They also compare our result on the basis of the above five parameters and the result is better in comparison to the traditional technique.

In 2012, Xu Guanlei et al. [27] investigates how the bi-dimensional empirical mode decomposition (BEMD) behaves in digital images.. The three-dimensional cubes disclosing the performance of BEMD are presented, which turn out to be in good agreement with intuition and physical interpretation. The theoretical analysis is provided for analyzing the observed behaviors and supported by numerical experiments. The main aim of their study is primarily to contribute to a better understanding of the possibilities and limitations offered by BEMD in digital images.

In 2012, Zhang et al. [28] suggest that the image is denoised first and is then interpolated. The denoising process, however, may destroy the image edge structures and introduce artefacts. Meanwhile, edge preservation is a critical issue in both image denoising and interpolation. To address these problems, authors propose a directional denoising scheme, which naturally endows a subsequent directional interpolator. Compared with the conventional schemes that perform denoising and interpolation in tandem, the proposed noisy image interpolation method can reduce many noise-caused interpolation artefacts and preserve well the image edge structures.

In 2013, Vikas Gupta et al.,[29] presents a review of some noteworthy work in the area of image denoising. The popular approaches are categorized into different sets and an overview of different algorithms and analysis is presented.

In 2013, Jignasa M. Parmar et al. [30] have evaluated and compared performances of modified denoising method and the local adaptive wavelet image denoising method. These methods are compared with other based on PSNR (Peak signal to noise ratio) between original image and noisy image and PSNR between original image and denoised image. Their Simulation and experiment results for an image demonstrate that RMSE of the local adaptive wavelet image denoising method is least as compare to modified denoising method and the PSNR of the local adaptive wavelet image denoising method is high than other method. Therefore, the image after denoising has a better visual effect.

In 2013, Kheradmand et al. [31] present an analysis for the filtering behavior of the proposed method based on the spectral properties of Laplacian matrices. Some of the well-established iterative approaches for improving kernel-based denoising like diffusion and boosting iterations are special cases used in author’s framework. Their proposed approach provides a better understanding of enhancement mechanisms in self-similarity-based methods, which can be used for their further improvement.

3. Proposed Work

We are presenting a new method of denoising based on linear threshold expansion. Gaussian Noise having probability density function (PDF) equal to that of the normal distribution which represents the statistical noise parameter which is also known as the Gaussian distribution. The function p,probability density function (PDF) with a random variable(Gaussian Random variable) z is given by:

$$P_G(z) = \frac{1}{\sigma\sqrt{2\Pi}e^{\frac{-(Z-\mu)^2}{2\sigma^2}}}$$

μ and σ represents the mean and standard deviation respectively. The special variant of this noise is white Gaussian noise, in which the values at any pair of times are identically distributed and statistically independent . It is used to produce additive white Gaussian noise. Due to signal transmission, temperature and poor illumination this type of noise is arises in digital images. So our denoising process starts with F(x) with a linear threshold expansion:

$$F(X) = \sum_{n=1}^{N} F_n a_n$$

a_n is the unknown weight assigned at the run time, n is the length of the number of pixels.

For example, a filtered Input image block, B, can be calculated as

$$\sum F_v F_l A_i$$

where A_i are neighboring image blocks which have contribution to the target output block, F_v is the vertical filter and F_l the horizontal filters. We first extract each row from an image block by multiplying with a special pre-matrix Wi , defined as

$$Wi\ (k, l) = \delta\ (k - i, l - i)$$

There is only one non-zero element in the matrix. Wi extracts the i-th row of image block A and set all remaining rows to zeros. After this step, we shift each row independently with the correct distance (as required by the shearing operation) by post-multiplying with a column shifting matrix. For example, the following N by (i+N) matrix Mi shifts the original N by N matrix to the right by i columns and pad zeroes in the first i columns.

Mi = [i zero columns | I | . . .]

where I is the N by N identity matrix. In practical implementations of shearing and rotation, interpolation (i.e., filtering) and resampling are also

performed. We are considering the multi-dimensional interpretation of edge-preserving filters [Barash 2002]. Let I : ΩÇR^2→R^3
2D RGB color image, defining a 2D manifold M_I in R5 [Kimmel et al. 1997]. Also, let ^p = (xp; yp; rp; gp; bp) M_I be a point on this manifold. ^p has a corresponding pixel in I with spatial coordinates p = (xp; yp) and range coordinates I(p) = (rp; gp; bp). Let F(^p; ^q) be an edge-preserving filter kernel in 5D. J, the image obtained when filtering I with F can be expressed as

J(p) =Z$\int_{\Omega}$ I(q) F(^p; ^q) dq
Where R F (^p; ^q) dq = 1.

We are considering Decomposition (DE) and Reconstruction (RE) parameters for the transformation domain denoising.

DE=$(d_{i,j})_{(I,j)}$
RE=$(r_{i,j})_{(I,j)}$
Apply DE to the noisy signal

Y= X+b
To get the transformed noisy coefficient
W=DY$(W_i)_i$€ [1:L]
Apply point wise thresholding function
$\beth(w) = (\theta_i(W_i))i$ €$[1{:}L]$
Then we revert the original domain by applying RE
$\in_{\bar{X}}$=R Ǿ(W)

Addtitive Gaussian white noise can be removed using the inter-scale linear threshold edge principle in the framework of an orthonormal wavelet transform (OWT) only. The wavelet transform is included in the process.
The wavelet series expansion of function $f(x) \in L^2(\mathbf{R})$ relative to wavelet $\psi(x)$ and scaling function $\phi(x)$. It can be written as

$$f(x) = \sum_k c_{j_0}(k)\phi_{j_0,k}(x) + \sum_{j=j_0}^{\infty}\sum_k d_j(k)\psi_{j,k}(x)$$

where j_0 is an arbitrary starting scale and the $c_{j_0}(k)$'s are normally called the approximation or scaling coefficients, the $d_j(k)$'s are called the detail or wavelet coefficients. The expansion coefficients are calculated as

$$c_{j_0}(k) = \left\langle f(x), \tilde{\phi}_{j_0,k}(x)\right\rangle = \int f(x)\tilde{\phi}_{j_0,k}(x)dx$$
$$d_j(k) = \left\langle f(x), \tilde{\psi}_{j,k}(x)\right\rangle = \int f(x)\tilde{\psi}_{j,k}(x)dx$$

If the function being expanded is a sequence of numbers, like samples of a continuous function $f(x)$. The resulting coefficients are called the discrete wavelet transform (DWT) of $f(x)$. Then the series expansion defined becomes the DWT transform pair

$$W_\phi(j_0,k) = \frac{1}{\sqrt{M}}\sum_{x=0}^{M-1} f(x)\tilde{\phi}_{j_0,k}(x)$$
$$W_\psi(j,k) = \frac{1}{\sqrt{M}}\sum_{x=0}^{M-1} f(x)\tilde{\psi}_{j,k}(x)$$

for $j \geq j_0$ and

$$f(x) = \frac{1}{\sqrt{M}}\sum_k W_\phi(j_0,k)\phi_{j_0,k}(x) + \frac{1}{\sqrt{M}}\sum_{j=j_0}^{\infty}\sum_k W_\psi(j,k)\psi_{j,k}(x)$$

where $f(x)$, $\phi_{j_0,k}(x)$, and $\psi_{j,k}(x)$ are functions of discrete variable x = 0, 1, 2, ... , $M - 1$.

Peak signal-to-noise ratio (PSNR) is a ratio between the maximum power of a signal and the power of distorting noise that affects the quality of its representation of the signal or the image. The block of PSNR computes the peak signal-to-noise ratio between two images. The unit of PSNR is in decibels. This ratio is the measurement of noisy images in comparison to the denoised images. The higher the PSNR, the better the quality of the final image or the denoised image achieved. The *Mean Square Error (MSE)* and the *Peak Signal to Noise Ratio (PSNR)* are the two error metrics used to compare the quality of noisy in comparison to the denoised image. The MSE represents the cumulative squared error between the compressed and the original image, whereas PSNR represents a measure of the peak error. The lower the value of MSE, the better the quality of the final image or the denoised image achieved.
To compute the PSNR, the block first calculates the mean-squared error using the following equation:

$$\mathrm{MSE} = \frac{\sum_{M,N}[I_1(m,n) - I_2(m,n)]^2}{M * N}$$

The M and *N* are the number of rows and columns in the input images, respectively. Then the block computes the PSNR using the following equation:

$$\mathrm{PSNR} = 10\log_{10}\frac{X^2}{\mathrm{MSE}}$$

The *R* is the maximum fluctuation in the input image data type. For example, if the input image has a double-precision floating-point data type, then *R* is 1. If it has an 8-bit unsigned integer data type, *R* is 255, etc.

4. Result Analysis

The performance of both method for denoising of image were tested on set of grayscale images such as Lena image, Peppers, boat etc. at noise variance 0.05. Here, in this paper for the performance we consider the images with the resolution of 256×256 and 512 * 512. The quality of an image is examined by various metrics used for objective evaluation of an image. Some of them are root mean square error (RMSE) and peak signal to noise ratio (PSNR). The results show the effectiveness of our approach. Table 1 shows the comparison from our method with the traditional technique [36]. Table 2 shows the results from our proposed work. The results show by our approach having improved PSNR as comparison to the traditional technique.

Table 1: Results [36]

Images	**Image Denoising[36]**	
	RMSE	PSNR
Leena	15.48	24.33
Peeper	19.44	22.35

Table 2: Results [Proposed Work]

Images	**Noisy Image**		**Proposed Work**	
	RMSE	PSNR	RMSE	PSNR
Leena 256 * 256	49.48	18.41	15.71	23.62
Leena 512 * 512	50.40	17.86	12.53	25.63
Peeper 256 * 256	48.97	18.46	16.99	24.70
Peeper 512 * 512	50.30	18.15	13.13	26.98

5. Conclusion

Denoising algorithm's measure is considered power the quantitative bill tuition such as signal-to-noise index (SNR) and peak signal-to-noise ratio (PSNR) as well as visual quality of images. Currently, gaussian channel divide up behind be assumed for many techniques. This may groan be everlastingly actual instead of opening of noise and nature varied sources of noise. We have presented a row based arrangement for image extraction. The methodology we have adopted is Wavelet based Linear Gaussian Image Denoising. We have calculated PSNR and RMSE value for comparison.

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