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Local Altered and Optimized Center Pixel Weights for Image Denoising

Madhu Gujjala
M.Tech student in Communication Systems,
Vignana Bharathi Institute of Technology.

S. A. Mansoor
Assistant Professor,
Vignana Bharathi Institute of Technology.

ABSTRACT:

Now a day's digital image processing applications are widely used in various fields such as medical, military, satellite, remote sensing and even web applications also. In any application image denoising is a challenging task because noise removal will increase the digital quality of an image and will improve the perceptual visual quality.

In this paper we proposed a new method "local altered and optimized center pixel weights (LAOCPW) with non local means" to improve the denoising performance of digital color image sequences. Simulation results show that the proposed method has given the better performance when compared to the existing algorithms in terms of peak signal to noise ratio (PSNR) and mean square error (MSE).

I.INTRODUCTION:

Images captured from both digital cameras and conventional film cameras will affected with the noise from a variety of sources. These noise elements will create some serious issues for further processing of images in practical applications such as computer vision, artistic work or marketing and also in many fields. There are many types of noises like salt and pepper, Gaussian, speckle and passion. In salt and pepper noise (sparse light and dark disturbances), pixels in the captured image are very different in intensity from their neibouring pixels; the defining characteristic is that the intensity value of a noisy picture element bears no relation to the color of neibouring pixels. Generally this type of noise will only affect a small number of pixels in an image. When we viewed an image which is affected with salt and pepper noise, the image contains black and white dots, hence it terms as salt and pepper noise. In Gaussian noise, noisy pixel value will be a small change of original value of a pixel.

A histogram, a discrete plot of the amount of the distortion of intensity values against the frequency with which it occurs, it shows a normal distribution of noise. While other distributions are possible, the Gaussian (normal) distribution is usually a good model, due to the central limit theorem that says that the sum of different noises tends to approach a Gaussian distribution.

In selecting a noise reduction algorithm, one must consider several factors:

• A digital camera must apply noise reduction in a fraction of a second using a tiny on board CPU, while a desktop computer has much more power and time.

• whether sacrificing some real detail information is acceptable if it allows more distortion or noise to be removed (how aggressively to decide whether the random variations in the image are noisy or not)

In real-world photographs, maximum variations in brightness ("luminance detail") will be consisted by the highest spatial frequency, rather than the random variations in hue ("chroma detail"). Since most of noise reducing techniques should attempt to remove noise without destroying of real detail from the captured photograph.

In addition, most people find luminance noise in images less objectionable than chroma noise; the colored blobs are considered "digital-looking" and artificial, compared to the mealy appearance of luminance noise that some compare to film grain. For these two reasons, most of digital image noise reduction algorithms split the image content into chroma and luminance components.

One solution to eliminate noise is by convolving the original image with a mask that represents a low-pass filter or smoothing operation. For example, the Gaussian mask incorporates the elements determined by a Gaussian function. This operation brings the value of each pixel into closer harmony with the values of its neighbours. In general, a smoothing filter sets each pixel to the mean value, or a weighted mean, of itself and its nearby neighbours; the Gaussian filter is just one possible set of weights. However, spatial filtering approaches like mean filtering or average filtering, Savitzky filtering, Median filtering, bilateral filter and Wiener filters had been suffered with loosing edges information. All the filters that have been mentioned above were good at denoise of images but they will provide only low frequency content of an image it doesn't preserve the high frequency information. In order to overcome this issue Non Local mean approach has been introduced.

More recently, noise reduction techniques based on the "NON-LOCAL MEANS (NLM) had developed to improve the performance of denoising mechanism [1][4][5][9]. It is a data-driven diffusion mechanism that was introduced by Buades et al. in [1]. It has been proved that it's a simple and powerful method for digital image denoising. In this, a given pixel is denoised using a weighted average of other pixels in the (noisy) image. In particular, given a noisy image n_i, and the denoised image d̂=(d_i) at pixel i is computed by using the formula.

$$\hat{d}_i = \frac{\sum_j w_{ij} n_j}{\sum_j w_{ij}} \qquad (1)$$

Where w_ij is some weight assigned to pixeli and j. The sum in (1) is ideally performed to whole image to denoise the noisy image. NLM at large noise levels will not give accurate results because the computation of weights of pixels will be different for some neibourhood pixels which looks like same. Most of the standard algorithm used to denoise the noisy image and perform the individual filtering process.

Denoise generally reduce the noise level but the image is either blurred or over smoothed due to losses like edges or lines. In the recent years there has been a fair amount of research on center pixel weight (CPW) for image denoising [3], because CPW provides an appropriate basis for separating noisy signal from the image signal. Optimized CPW is good at energy compaction, the small coefficient are more likely due to noise and large coefficient due to important signal feature [8].

These small coefficients can be thresholded without affecting the significant features of the image. The proposed local altered and optimized CPW correspond to its continuous version sampled usually on a dyadic grid, which means that the scales and translations are power of two [5]. Local altered and optimized CPW is a simple non-linear technique, which operates on one weighted coefficient at a time. Experiments show the effectiveness of the new technique both in terms of peak signal-to-noise ratio (on simulated noisy images) and of subjective quality (on actual images).

In this letter, we discuss the CPW problem with NLM and propose new optimized solution "local altered and optimized CPW (LAOCPW)". The rest of this thesis has been organized as: Section II existing techniques such as Savitzky-golay, median, bilateral, wavelet filters, and NLM; Section III discusses the new optimized solution of the CPW problem; Section IV shows experimental comparisons for various techniques with the new solution; and Section V concludes the thesis.

II.EXISITING TECHNIQUES:

In this section we discussed various spatial filters and their performance when a noisy input will be given to them. Here in this section we had explained about each filter in detail.

a.Savitzky-Golay Filter:

It is a simplified method and uses least squares technique for calculating differentiation and smoothing of data. Its computational speed will be improved when compared least-squares techniques. The major drawback of this filter is: Some of first and last data point cannot smoothen out by the original Savitzky-Golay method. Assuming that, filter length or frame size (in S-G filter number of data sample read into the state vector at a time) N is odd, N=2M+1 and N= d+1, where d= polynomial order or polynomial degree.

b.Median filter:

This is a nonlinear digital spatial filtering technique, often used to removal of noise from digital images. Median filtering has been widely used in most of the digital image processing applications.

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The main idea of the median filter is to run through the image entry by pixel, replacing each pixel with the median value of neighboring pixels. The pattern of neighbors is called the "window", which slides, pixel by pixel, over the entire image.

c.Bilateral Filter:

The bilateral filter is a nonlinear filter which does the spatial averaging without smoothing edges information. Because of this feature it has been shown that it's an effective image denoising algorithm. Bilateral filter is presented by Tomasi and Manduchi in 1998. The concept of the bilateral filter was also presented in [8] as the SUSAN filter and in [3] as the neighborhood filter. It is mentionable that the Beltrami flow algorithm is considered as the theoretical origin of the bilateral filter [4] [5] [6], which produce a spectrum of image enhancing algorithms ranging from the linear diffusion to the non-linear flows. The bilateral filter takes a weighted sum of the pixels in a local neighborhood; the weights depend on both the spatial distance and the intensity length. In this way, edges are preserved well while noise is eliminated out.

d.Wavelet Filtering:

Signal denoising using the DWT consists of the three successive procedures, namely, signal decomposition, thresholding of the DWT coefficients, and signal reconstruction. Firstly, we carry out the wavelet analysis of a noisy signal up to a chosen level N. Secondly, we perform thresholding of the detail coefficients from level 1 to N. Lastly, we synthesize the signal using the altered detail coefficients from level 1 to N and approximation coefficients of level N. However, it is generally impossible to remove all the noise without corrupting the signal. As for thresholding, we can settle either a level-dependent threshold vector of length N or a global threshold of a constant value for all levels.

e.Classic Non local means:

It is a data-driven diffusion mechanism that was introduced by Buades et al. in [1]. It has been proved that it's a simple and powerful method for digital image denoising. In this, a given pixel is denoised using a weighted average of other pixels in the (noisy) image. In particular, given a noisy imagen_i, and the denoised image d ̂=(d_i ̂) at pixel i is computed by using the formula

$$\hat{d}_i = \frac{\Sigma_j w_{ij} n_j}{\Sigma_j w_{ij}} \quad (1)$$

Where w_ij is some weight assigned to pixeli and j. The sum in (1) is ideally performed to whole image to denoise the noisy image. NLM at large noise levels will not give accurate results because the computation of weights of pixels will be different for some neibourhood pixels which looks like same.

$$w_{l,j} = exp\left(\Sigma_{k\epsilon P} G_\beta \left(\left(n_{l+k} - n_{j+k}\right)^2 / 2h\right)\right) \quad (2)$$

In this each weight is computed by similarity quantification between two local patches around noisy pixels n_land n_j as shown in eq. (2). Here, G_βis a Gaussian weakly smooth kernel [1] and P denotes the local patch, typically a square centered at the pixel and h is a temperature parameter controlling the behavior of the weight function.

III.PROPOSED OPTIMIZED CPW:
A.Existing Center Pixel Weights :

The CPW in the classic NLM is unitary, because (2) implies w_(l,j) =1 for alll1. However, it has been reported that this unitary CPW will not perform well in many events [7]. Indeed, if an image will be affected with higher levels of noise it gives poor performance when the noisy pixel dominates in the recovered pixel. In improver to this CPW, several other CPWs had been proposed and merged with in the NLM community to enhance the system performance. These include the zero CPW (3), the Stein CPW (5), and the max CPW (6). These CPWs are of two groups: global CPWs (3), (4) and local CPWs (5), (6). The global CPWs use a constant center pixel weights for every pixel, while the local will vary for all pixels. In the further section, we will show that all of the above mentioned CPWs had failed to take all variables into consideration and therefore we exaggerate the CPW problem.

$$\vartheta_l^{zero} = 0 \quad (3)$$

$$\vartheta_l^{one} = 1 \quad (4)$$

$$\vartheta_l^{stein} = \exp\left(-\sigma^2 |P|/h\right) \quad (5)$$

$$\vartheta_l^{max} = \max\left(w_{l,j}\right) \quad (6)$$

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B.Shrinkage Estimator:

To fully expose the CPW problem, we separate the contributions of the center and of the non-center pixels in the Non Local Means denoised pixel (d_l ̂) in (2)

$$\hat{d}_l = \frac{W_l}{W_l+\vartheta_l}\hat{z}_l + \frac{\vartheta_l}{W_l+\vartheta_l} n_l \qquad (7)$$

Where W_l is the sum all non-center pixels?

$$W_l = \sum_{j\in S\backslash\{l\}} w_{l,j} \qquad (8)$$

And $\hat{z}_l$ is the denoised pixel by using all non-center weights.

$$\hat{z}_l = \sum_{j\in S\backslash\{l\}} w_{l,j} n_j / W_l \qquad (9)$$

If we are given an optimized (d_l ̂) and solve for _l, we can see that the optimized _lis a function of W_l, (z_l) ̂, n_l. Thus a Center pixel weights does not consider all the variables. Here we notice that the global CPWs neglect all three variables form the CPW function, while the local CPW neglects n_l.

Let ρ_l be a fraction of the contribution of the center pixel n_l in $\hat{d}_l$, namely

$$\rho_l = \vartheta_l / (\vartheta_l + W_l) \qquad (10)$$

Accordingly, the NLM-CPW problem in (7) can be rewritten as

$$\hat{d}_l = (1-\rho_l)\hat{z}_l + \rho_l n_l \qquad (11)$$

Eq. (11) is so called shrinkage estimator, which can be an improved version of existing estimators by using the input data.

C. The James-Stein Center Pixel Weight

This is a classic solution which minimizes the risk of estimation in terms of the error and the corresponding new estimator is derived as follows

$$\hat{x}^{JS} = (1-\rho^{JS})\hat{z} + \rho^{JS} n \qquad (12)$$

Where,

$$\rho^{JS} = 1 - (m-2)\sigma^2 / \|n - \hat{z}\|^2 \qquad (13)$$

A.Proposed Local Altered and optimized Center Pixel Weights

Although the James-Stein CPW considers all the variables in the CPW function, it still a global CPW and will gives a monovular weight to all pixels.

However, instead of unbiased for each pixel the denoised process will be always biased. Thus, ideally we want a local altered and optimized CPW for every pixel. One possible solution is to replace the n-z ̂ in (12) withn-z ̂ ^2, but it leads to an unstable solution, because of the faulty point-wise estimation. Alternatively, we can divide the input image into several blocks and thus the JSCPW (13) will be computed for each local block which interns a local altered and optimized CPW will be adapted to every pixel.

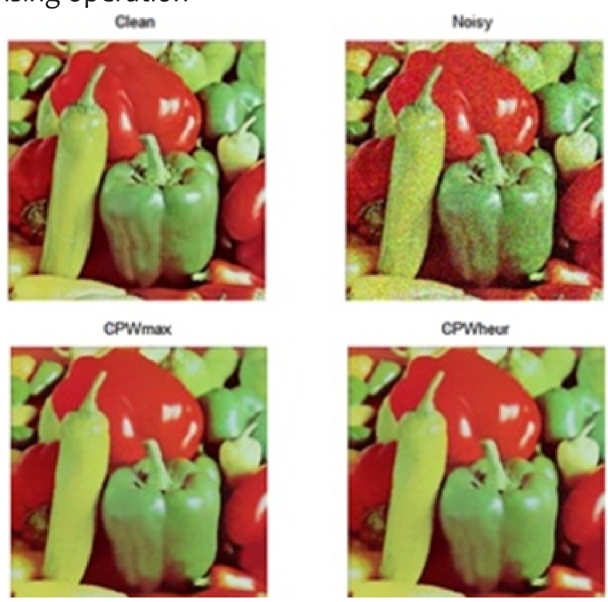
$$\rho_l^{LAO} = 1 - (|B|-2)\sigma^2 / \|nb_l - \hat{z}b_l\|^2) \qquad (14)$$

In this way, we derived and constructed a new local altered and optimized CPW at each and every pixel, and thus the pixels will be denoised by using LAOCPW, it can be written as

$$\hat{x}_l^{LAO} = (1-\rho_l^{LAO})\hat{z} + \rho_l^{LAO} n_l \qquad (15)$$

IV.SIMULATION RESULTS:

All the following simulations are done under the MATLAB R2011a environment with Intel Core i3 CPU at 4.0 GHz. We compared the performance evaluation of existing CPWs with the proposed LAOCPW algorithm under the classic Non-Local Means framework (only the CPW is changed). In particular, we set the search region to 30×30 square, and 14x14 B centered on the local pixel, and test performance for 3x3, 5x5and 7x7 patches , respectively. Here gray scale and colored images both have been taken into consideration with additive Gaussian noises. Then the denoising performance will be evaluated by calculating the PSNR, which is used to measure the quality of the recovered image after denoising operation



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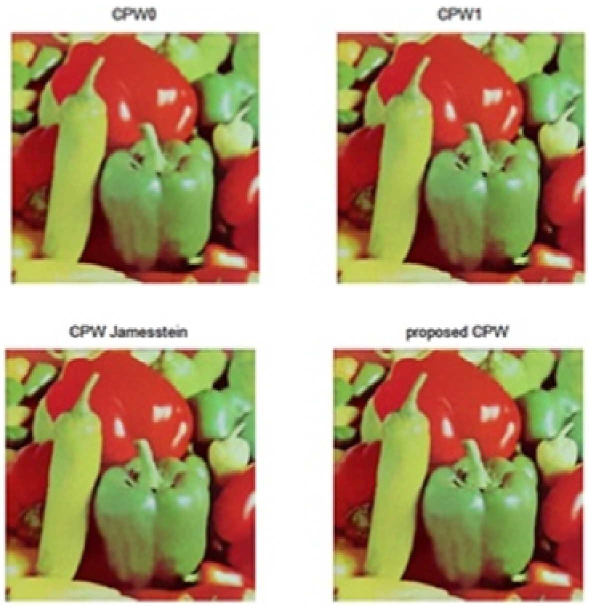
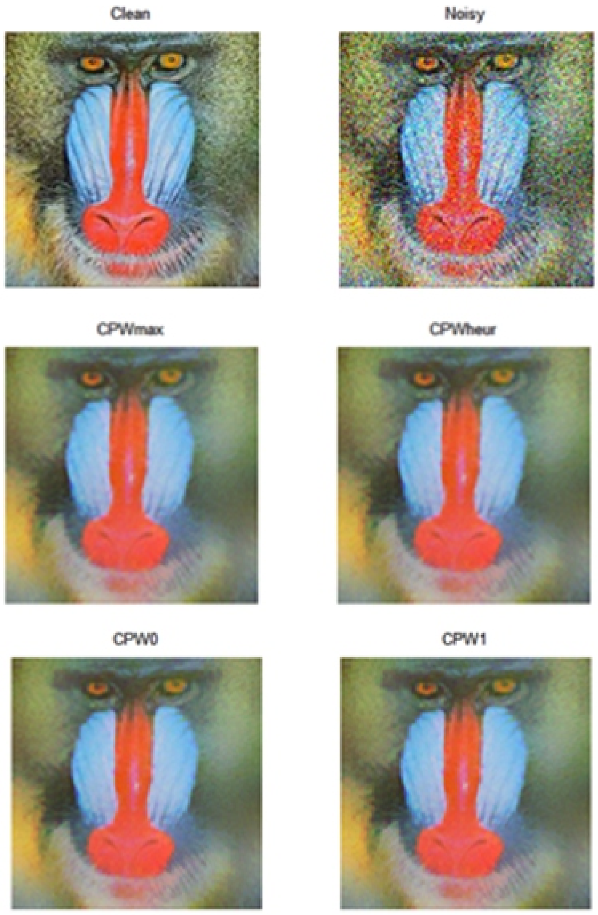


Fig.2. Performance results of existing and proposed CPWs for "vegetable"



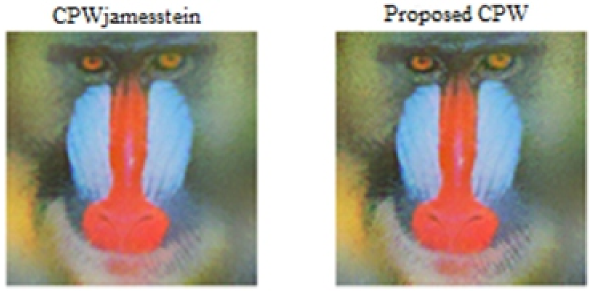
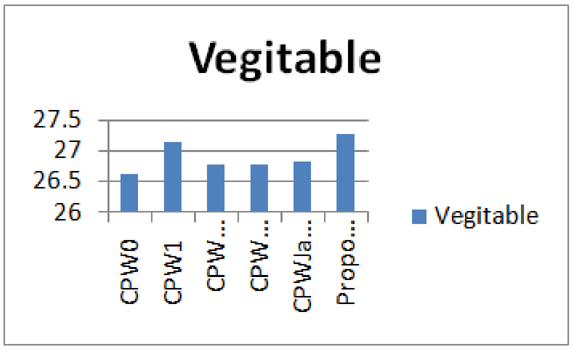
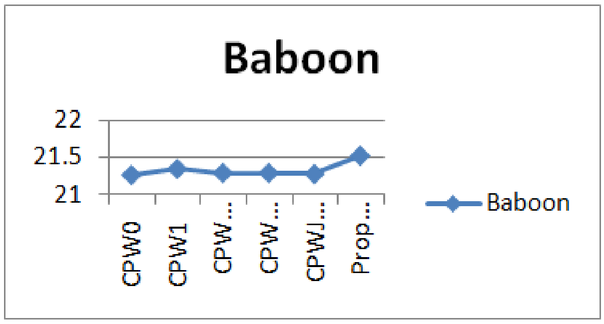


Fig.3. Performance results of existing and proposed CPWs for "baboon"



(a)



(c)

Fig.6. (a) and (b) Comparison of PSNR values for existing and proposed CPWs for four test image

V.CONCLUSION:

In this letter, a simple and unique method has been proposed to address the issue of image recovery from its noisy counterpart. It is based on the local altered and optimized center pixel weight algorithm and overcomes the existing CPW problem which occurs in classical NLM filtering and shrinkage estimator. This proposed method of denoise algorithm produce overall better psnr result compared with other traditional denoises approaches under various large noise levels.

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