Adaptive Image Denoising Based on MACWM and NLEM Filters

Haider K. Hoomd

Huda A. Abduljabbar **Ahmed Abd Ali Abdulkadhim**

Sahar H. Hashim

Ahmed198643@yahoo.com

Al-Mustanisriyah University –Education college – Computer science Dept.

Abstract

High range types of noise can infect and corrupt digital images. Of these Noise types is the resulted from errors in the image acquisition process. This error change pixel values that not reflect the true intensities and image details vision. Several ways that noise can be introduced into an image, most of them depending on how the image is created or transmit through the network. In this paper, new proposed modifications added to Modified Adaptive Center Weighted Median filter MACWM to achieve the high accuracy in noise detection and removing especially when image corrupted by multi noise types. None Local Euclidean Median (NLEM) and Mean filters were added in these proposed modifications improved the noise wide spectrum detection. Good vision results produce from experiment the proposed system with less blur.

Keyword: image denoising, NLEM, MACWM, adaptive filters.

رفع ضوضاء صورة متكيف بالاعتماد على مرشحات MACWM و NLEM

حيدر كاظم حمود

هدى عبداللطيف عبدالجبار **احمد عبدعلي عبد الكاظم**

سحر حسن هاشم

الخلاصة

انواع متعددة من الضوضاء يمكن أن تصيب والصور الرقمية. من هذه الأنواع الضوضاء هو تنتجت عن أخطاء في عملية الحصول على الصور. وان هذه القيم للضوضاء تغير قيم البكسل الذي لا يعكس رؤية تفاصيل الصورة الحقيقية. العديد من الطرق يمكن إدخال الضوضاء إلى صورة، ومعظمها معتمدا على كيفية إنشاء صورة أو نقل من خلال الشبكة. في هذه البحث، وأضيفت تعديلات جديدة مقترحة لتعديل مرشح MACWM لتحقيق درجة عالية من الدقة في الكشف عن الضوضاء وإزالة خصوصا عندما الصورة افسدتها أنواع متعددة من الضوضاء. في هذه التعديلات المقترحة اضيفت مرشح NLEM و مرشح المعدل لتحسين الكشف عن طيف واسع من الضوضاء. النتائج من تجربة النظام المقترح كانت لديها رؤية جيدة مع أقل طمس.

1. Introduction

Digital images may damage by various noise types (like impulse noise) during Image acquisition, transmission through network and other processing. Usually noise corrupts images by changing some of the original image pixels with new pixels having color values differ and dynamic luminance range.[1]

Because of its effective noise suppression capability and high computational efficiency, the median filter is used widely in impulse noise removal. However, it uniformly changes every pixel value by the median of its neighbor’s values. Consequently, when the window size is large some image details are removed. [2]

Important feature of None Local Mean (NLM) filter is appears more like white noise comparing to other denoising techniques such as(wavelet regularization, total variation denoising, anisotropic diffusion, and Gaussian smoothing [3].

At large noise levels, the denoising accuracy of Non-Local Means (NLM) improved by replacing the mean by the Euclidean median and calls Non-Local Euclidean Medians (NLEM). NLEM performs better than NLM in the vicinity of edges when large noise levels in image. The efficiently implementation of NLEM filter can be by using iteratively reweighted least squares.[3]

Another denoising filter is, adaptive center weighted median (ACWM) filter that used to avoids the errors and drawbacks of the CWM filters. It designs to be changing between the median filters and input data, result data will be clustered by scalar quantization (SQ) method. Modified adaptive center weighted median (MACWM) filter use FCM method in clustering processing. [1]

In this paper, the two stage modifications added to the MACWM to achieve the high accuracy of noise detection and removal. The modification §re using the NLEM and mean filters in order to increase the noise spectrum can be detected and removed.

2. Adaptive Center-Weighted Median Filtering[1]

Let $F = \{(F_1 , F_2)|1 \le F_1 \le P,\ 1 \le F_2 \le Q\}$ describe the noisy image pixels coordinates that corrupted by impulsive noise. Let P is image height and Q is the image width, while the x(f) denote the input noisy image pixel value. This x(f) is at location f∈ F. At each location f, the observed filter window L{f} whose size is N = 2n + 1 (n is an integer);.

$$L\{f\} = \{x_S (f) : s = 1,2,...,n, n+1,..., N\} \quad (1)$$

Where the center pixel input pixel is $x(f) = x_{n+1}$. Figure 1 shows a 3×3 filter window.

$x_1(f)$	$x_2(f)$	$x_3(f)$
$x_4(f)$	$x_5(f)$	$x_6(f)$
$x_7(f)$	$x_8(f)$	$x_9(f)$

Figure 1. The filter window with center $x(f)=x_5(f)$.

3. MACWM Filter Structure [1]

Figure 2 is illustrates the framework of the MACWM filter. It is composed of four parts: set of threshold by FCM, training block the center weight (using LMS algorithm), median filter, and a decision of noises exist or not.

At first, input image median will be computed. FCM algorithm is partition input image (observation vector space) to B block, and give blocks related weights by trained using the LMS algorithm. y(f) vector is the output value of the MACWM filter after processed pixel x(f) is obtained using follows:

$$y(f) = (1 - w(f))x(f) + y(f)\ \mathrm{me}(f) \qquad (2)$$

Median filter output value is denoted as me(f) at k in a filter window as follows:

$$me(f) = ME\{x_1(f),..., x_N(f)\} \quad ME \text{ is median operation}$$

(3)

The linear combinations of the weighted output of the median filter and the related weighted input signal give the MACWM filter its effect. Here, w (f) view the membership function indicating to noise corruption (w(f)=1) or not (w(f)=0) depended on location of the pixel x(f). The output value when (w(f)=1) of MACWM filter is equal to me(f) otherwise is equal to x(f).

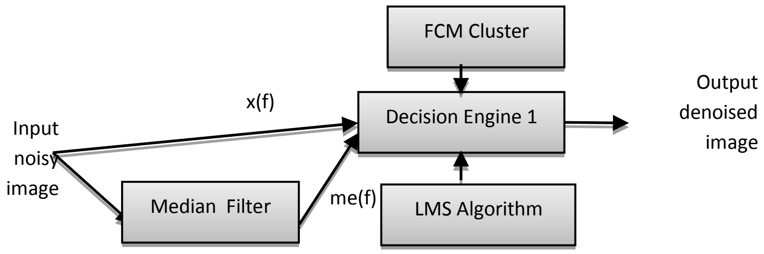

Figure 2. The MACWM filter basic structure

3.1 FCM Structure [1]

Fuzzy clustering models are Fuzzy C-Means (FCM) widely used. The FCM algorithm assigns memberships to which are inversely related to the relative distance of to the point prototypes that are cluster centers in the FCM model. Objective function in FCM is

$$J_m(U,V) = \sum_{k=1}^{n} \sum_{i=1}^{c} u_{ik}^{m} \|x_k - v_i\|^{p} \qquad (4)$$

Where $V = \{vi,\ i = 1,2,...,\ c\}, U = \{u^{m}\ ik\}$ are centers and membership functions and are $X = \{x_i ,..., x_n\} \subset R^S$ data's. $v \in R^S$ is center of ith centers. $u_{ik} \in [0,1]$ is membership of ith data to kth centers. N samples are clustered to c cluster as following constraints are satisfied.

$$M_{fcm} = \left\{ U \in R^{c*n} \left| \begin{array}{l} \forall i,k : 0 \le u_{i,k} \le 1; \\ \sum_{i=1}^{c} u_{ik} = 1, \sum_{k=1}^{n} u_{ik} > 0 \end{array} \right. \right\}$$

(5)

Optimization procedure gives,

$$v_i = \frac{\sum_{k=1}^{n} (u_{i,k})^m x_k}{\sum_{k=1}^{n} (u_{i,k})^m},$$

$$u_{ik} = \sum_{l=1}^{c} \left(\frac{\|Y_k - v_i\|}{\|Y_k - v_l\|} \right)^{-2/(m-1)} \qquad (6)$$

3.2 LMS algorithm

Least Mean Square algorithms are a class of adaptive filter used to mimic a desired filter by finding the filter coefficients that relate to producing the least mean squares of the error signal (difference between the desired and the actual signal).

LMS algorithm is formulated from the error equation. The terms "error cancellation" is called optimum if the process only results minimum error in the processed signal. Hence, this definition is used to formulate LMS algorithm as seen below: [4]

$$\begin{aligned}\varepsilon_k &= d_k - y_k \\ &= d_k - \mathbf{X}_k^T\mathbf{W} \\ &= d_k - \mathbf{W}^T\mathbf{X}_k \\ \varepsilon_k^{\,2} &= d_k^{\,2} + \mathbf{W}^T\mathbf{X}_k\mathbf{X}_k^T\mathbf{W} - 2d_k\mathbf{X}_k^T\mathbf{W}\end{aligned} \qquad (7)$$

As E[$\mathbf{X_k X_k}$] = **R** and E[$\mathbf{d_k X_k}$] = **P**, then:

$$\xi = E[\varepsilon_k^{\,2}] = E[d_k^{\,2}] + \mathbf{W}^T\mathbf{R}\mathbf{W} - 2\mathbf{P}^T\mathbf{W} \qquad (8)$$

Which **R** denotes autocorrelation of input signal x_k and **P** denotes cross correlation between desired response d_k and x_k.

3.3 Non-Local Euclidean Medians

The NL-means not only compares the grey level in a single point but the geometrical configuration in a whole neighborhood. This fact allows a more robust comparison than neighborhood filters. [6]

The Non-Local Euclidean Medians (NLEM) is below. Where S(i) is denote to the search window of size S × S centered at pixel i. **[3]**

Algorithm 1 Non-Local Euclidean Medians

Input: Noisy image $u = (u_i)$, and parameters h, λ, S, k.
Return: Denoised image $\hat{u} = (\hat{u}_i)$.
(1) Estimate noise variance σ^2, and set $h = \lambda\sigma$
(2) Extract patch $P_i \in R^{k^2}$ at every pixel i.
(3) For every pixel i, do
(a) Set $w_{ij} = \exp(-\|P_i - P_j\|^2/h^2)$ for every $j \in S(i)$.
(b) Find patch P that minimizes $\sum_{j \in S(i)} w_{ij} \|P - P_j\|$.
(c) Assign $\hat{u}_i$ the value of the center pixel in P.

4. Mean filter [5]

The idea of mean filtering is simply to replace each pixel value in an image with the mean (`average') value of its neighbors, including itself. This has the effect of eliminating pixel values, which are unrepresentative of their surroundings. Mean filtering is usually thought of as a convolution filter. Like other convolutions it is based around a kernel, which represents the shape and size of the neighborhood to be sampled when calculating the mean. Often a 3×3 square kernel is used, as shown in Figure 3, although larger kernels (*e.g.* 5×5 squares) can be used for more severe smoothing. (Note that a small kernel can be applied more than once in order to produce a similar but not identical effect as a single pass with a large kernel.).

Computing the straightforward convolution of an image with this kernel carries out the mean filtering process.

$\frac{1}{9}$	$\frac{1}{9}$	$\frac{1}{9}$
$\frac{1}{9}$	$\frac{1}{9}$	$\frac{1}{9}$
$\frac{1}{9}$	$\frac{1}{9}$	$\frac{1}{9}$

Figure 3: 3×3 averaging kernel often used in mean filtering

5. The Proposed System

The main goal of this research is to reduce the noise in noisy image with minimum blur and enhancement effects. Previously researches were used many techniques to achieve noise removal operation. In this paper, Modified Adaptive Center Weighted Median (MACWM) filter (proposed in [1] and explain section 2)is modified by using the Non-Local Euclidean Median (NLEM) filter (proposed in [3] and explain in section3.3)in order to increase the accuracy of the noise selection and removing operation. The first modifications by adding the output of NLEM filter as a feed to the decision engine of the MACWM filter. The second modifications by adding the second stage of selection using the mean filter with decision engine 2 to set the output denoised image. Figure 4 shows the block diagram of the proposed system. The using this collection of filters is to remove various types of noise.

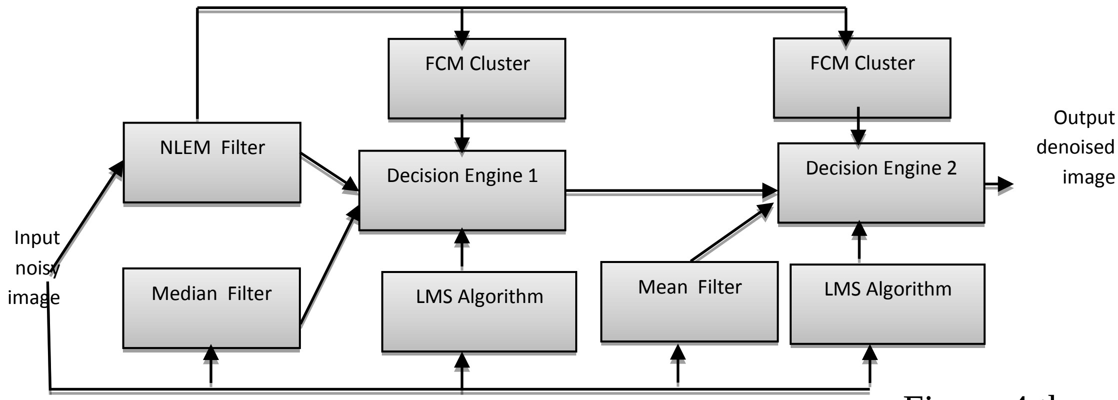

Figure 4 the block diagram of the proposed system

6. Experimental results

The proposed system is experimented by using 50 noisy image samples corrupted by deferent types of noise. The output results of the proposed system see how well it can remove the different types (like speckle noise, salt and pepper noise, and Gaussian noise) and enhance the image restoration with a good vision and less blur. Some of the proposed system experimental results are as shown in figure 5. Table 1 and 2 show the quality measurements of the proposed system outputs with different type of noise with two noise infection ratios (15% and 25%).

S1 noisy image

S1 denoised image

S2 noisy image

S2 denoised image

S3 noisy image

S3 denoised image

Figure 5 Some experimental results of the proposed system

Table 1 Some Experimental Results of the proposed system (with noise ratio 0.15)

Sample name	PSNR	Image Size	Noise type
S1	39.56	512x512	Salt-pepper
S2	38.24	512x 512	
S3	39.47	640x480	Gaussian, and Salt-pepper
S4	37.80	640x480	
S5	37.99	600x800	Speckle, and Salt-pepper
S6	36.90	600x800	
S1	38.60	600x800	Salt-pepper, Speckle, and Gaussian
S2	39.89	600x800	
S3	38.90	900x800	Speckle, and Gaussian
S4	41.46	1024x 900	

Table 2 Some Experimental Results of the proposed system (with noise ratio 0.25)

Sample name	PSNR	Image Size	Noise type
S1	33.11	512x512	Salt-pepper
S2	34.12	512x 512	
S3	32.78	640x480	Gaussian, and Salt-pepper
S4	35.65	640x480	
S5	35.01	600x800	Speckle, and Salt-pepper
S6	33.23	600x800	
S1	32.02	600x800	Salt-pepper, Speckle,

S2	31.00	600x800	and Gaussian
S3	35.45	900x800	Speckle, and Gaussian
S4	36.23	1024x 900	

6. Conclusion

In this paper, two stage modifications were added to the MACWM filter in order to increase the ability of the filter to detect high noise spectrum and remove them. Also, decrease the blurring effect after the denoising operation. With these modification framework; the image resulted from NLEM filter is classified into one of M mutually exclusive blocks for each stage, and then the weights $w_i(k)$ of membership function of impulsive corruption is indicated for the filtering operation. The NLEM and mean filters support the classification and decision engine (in both stages) with the classifier based on FCM clustering that produce good results in vision and measurements like PSNR with acceptable blurring edges even though multi-noise corruption. The Lager image size gives a good vision detail better than small image size.

References

[1] Hadi Sadoghi Yazdi and Faranak Homayouni**," Impulsive Noise Suppression of Images Using Adaptive Median Filter",** International Journal of Signal Processing, Image Processing and Pattern Recognition,Vol. 3, No. 3, September, 2010.

[2] Yiqiu Dong and Shufang Xu, "A New Directional Weighted Median Filter for Removal of Random-Valued Impulse Noise", IEEE Signal Processing Letters (Impact Factor: 1.64). 04/2007;
DOI: 10.1109/LSP.2006.884014

[3] Kunal N. Chaudhury and Amit Singer, **"Non-Local Euclidean Medians",** IEEE Signal Processing Letters, vol. 19(11), pp. 745 - 748, 2012.

[4] Udayanto Dwi Atmojo, **"Steepest Descent Least Mean Square Algorithm (LMS) Based Adaptive Filter for Noise Cancellation in Speech Signals"**, Proceedings of "The 6th SEAMS-UGM Conference 2011.

[5] Robert Fisher, Simon Perkins, Ashley Walker and Erik Wolfart, "**Hypermedia Image Processing Reference :Mean Filter"**, 2000 , http://homepages.inf.ed.ac.uk/rbf/HIPR2/mean.htm.

[6] Antoni Buades, Bartomeu Coll, and Jean-Michel Morel**," A non-local algorithm for image denoising"**, Computer Vision and Pattern Recognition, IEEE Computer Society Conference on, 20-25 June 2005,pp 60 - 65 vol. 2.