

A Statistical Image Noise Removal Adaptive Filter Using Rejection Test with F- Distribution

Dr. Abdulameer A. Kareem

ameer.aldelphi@yahoo.com

Prof. Dr. Abdul Monem S. Rahma

monemrahma@yahoo.com

Prof. Dr. Hilal H. salih

hhsrq@yahoo.com

Department of Computer Science / University of Technology

Abstract

The main characteristic of adaptive filters is that it alters its basic behavior as the image is processed, so it can remove noise from images regions as well as preserving edge and details information.

The objective of this work is to combine the statistical analysis methods and image processing techniques to increase image quality by removing the noise that corrupts it, so that the image will be ready for analysis and interpretation.

In this work a Statistical Image Noise Removal Adaptive Filter Using Rejection Test with F- Distribution is presented. The proposed filter removes noise from images corrupted by a variety type of noise effectively in such a manner it preserves image edges and details. Results shows that the proposed filter is much more accurate than many of the traditional and adaptive noise removal filters.

مرشح احصائي متكيف لأزالة الضوضاء من الصور باستخدام اختبار الرفض و توزيع F

الخلاصة

ان الخاصية الأهم للمرشحات المتكيفة (Adaptive Filters) هي انها تقوم بتعديل تصرفاتها الأساسية طبقاً للتغيرات التي تظهر أثناء معالجة الصورة ، وهي بذلك تقوم بأزالة الضوضاء من الصورة وبنفس الوقت تحافظ على حواف وتفصيل الصورة من الضياع.

الهدف من هذا البحث هو دمج طرق التحليل الاحصائي مع تقنيات المعالجة الصورية لتحسين نوعية الصورة من خلال ازالة الضوضاء التي تشوهها، وبذلك ستصبح الصورة الناتجة جاهزة لعملية التحليل والتفسير.

في هذا البحث تم تقديم مرشح أحصائي متكيف لأزالة الضوضاء من الصور باستخدام اختبار الرفض (Rejection Test) المعتمد على اختبار F . يمكن للمرشح المقترح أن يزيل الضوضاء من الصور المصابة بأنواع متعددة من الضوضاء بكفاءة عالية بحيث انه يحافظ على حواف وتفاصيل الصورة الدقيقة من الضياع. بينت النتائج ان المرشح المقترح يعطي نتائج أدق من العديد من المرشحات التقليدية والمتكيفة المستخدمة لأزالة الضوضاء.

1. Introduction

All image-acquisition processes are subjected to noise of some type, so there is little point in ignoring it, the ideal situation no-noise never occurs in practice.

The main problem with most of the conventional spatial filters (e.g. mean , median filters) , is that they perform the same calculations on all of the image pixels in the same manner, i.e. they deal with the image area's having high variation in pixel intensities (e.g. edge and boundaries) as they deal with image area's with fairly constant values (e.g. background) , thus this type of filters will remove noise from image, but at the same time they cause an adverse effects e.g. they blur image edges and smear image details .

Because of the wide availability of noisy images in practice , adaptive noise removal filters have acquired more attention, since adaptive filters remove noise from images as well as preserving edge information. Early works on adaptive noise removal use alpha-trimmed mean filter and minimum mean square error filter.

Recent research works have made effective progress to solve the noise problems. Jayaraj in 2009 presented a non-linear adaptive statistics estimation filter to remove high density Salt and Pepper noise. The algorithm detects the pixels corrupted by Salt an Pepper noise and replace them with a value estimated using his proposed algorithm. The algorithm detects the corrupted pixel at the initial stage itself [3].

Senthilrajan A. in 2010 presented an adaptive window size recursive weighted median filter (ARWMF) for removing the impulse noise in color images .The weights for the (RWMF) are calculated by using the median controlled algorithm. By applying region of interest (ROI) on selected windows the weight calculations efficiency can be increased and memory will be reduced [8].

Yazdi H. S. in 2010 presented a modified adaptive center weighted median (MACWM) filter with an adjustable central weight obtained by partitioning the observation vector space. Dominate points of the proposed approach are partitioning of observation vector space using clustering method. Training procedure using LMS algorithm then freezing weights in each block are applied to test image [11].

Ilango G in 2011 presented a different hybrid filtering technique for the removal of Gaussian noise, by topological approach. The filters are treated in terms of a finite set of certain estimation and neighborhood building operations. A set of such operations is suggested on the base of the analysis of a wide variety of non linear filters [2].

Kalavathy S. in 2011 presented a new filter called Switching Weighted Adaptive Median (SWAM) filter which used to incorporate the Recursive Weighted Median (RWM) filter and the Switching Adaptive Median (SAM) filter. The adaptive window size is selected using RWN and the output image produced by this filter with least mean square error is considered as input image to SAM filter where impulse detection mechanism is adopted [4].

Rahman M. M. 2012, presenting a filtering technique integrated statistical analysis of local features with median based noise adaptive filter, which differentiates the corrupted and uncorrupted pixels and processes only the corrupted ones in order to preserve the fine details of the image. The adaptive behavior of this filter enables it to adjust the filtering window based on the local noise density and facilitates the estimation of noise-free median values [7].

In this work the statistical methods and the image processing techniques are combined to increase image quality by removing the noise that corrupts it, so that the image will be ready for the next steps of image analysis and interpretation.

2. Rejection Test

When gathering data, we occasionally have a situations where one of these observations seems to differ from the other by an unusual amount and we may wish to reject it from our experiment , for this we would like to test whether this deviation is significant or whether it may be considered due to chance. This rejection test may be performed using the equation [10]:

$$t^2 = \frac{(\bar{x}_1 - \bar{x}_2)^2 (n_1 n_2) (n_1 + n_2 - 1)}{(n_1 S_1^2 + n_2 S_2^2) (n_1 + n_2)} \dots\dots\dots (1)$$

where n: the sample size

$n_1 = n - 1$ represent the sample size excluding the observation to be test.

$n_2 = 1$ represent the extent observation to be test.

S_1 = the standard deviation to the sample excluding the observation to be test.

S_2 = the standard deviation to the extent observation to be test.

The rejection test is developed to determine whether the extreme observations came from the same population as the other observations, or not. So the null and alternative hypothesis will be set up as given below:

H_0 : all observations came from the same population.

H_1 : extreme observation came from a different population.

Here the degrees of freedom are 1 and $n_1 - 1$; and $\alpha = 0.05$

First we obtain the value of $F_{n_1-1}^1$ from F table ; then we calculate the value of t^2 using equation (1). if $t^2 > F_{n_1-1}^1$ we reject the null hypothesis which says that the extreme observation came from the same population as other observations [10].

3. Noise Removal Filters

Noise is any undesired information that contaminates an image. Noise appears in images from a variety of sources. The digital image acquisition process which converts an optical images into a continuous electrical signal that is then sampled , is the primary process by which noise appears in digital images. At any step in the process there are fluctuations caused by natural phenomena that add a random value to the exact brightness value for a given pixel [9].

Digital images are corrupted by noise either during image acquisition ore during image transmission. The image acquisition noise is

photoelectronic noise (for photoelectronic sensors) or film-grain noise (in the case of photography). It can be proven that in both cases the noise is signal dependent. Let $f(x,y)$ be the original image that is recorded on a film slide. Let us denote by $g(x,y)$ the image that is observed if the Film is used as a transparency. The observed image is nonlinear transform of the original image, corrupted by multiplicative noise

$$g(x,y) = C (f(x,y))^{-\gamma} n(x,y) \dots\dots\dots (2)$$

The noise process $n(x,y)$ has a log-normal distribution [6].

In this case (signal dependent noise) it is obvious that the level of the noise value at each point in the image is a function of the grey level there. The grain seen in some photographs is an example of this sort of noise , and it is generally harder to deal with[5].

Signal-independent noise is a random set of grey levels, statistically independent of the image data; that is, added to the pixels in the image to give the resulting noisy image. This kind of noise occurs when an image is transmitted electronically from one place to another. If A is a perfect image and N is the noise that occurs during transmission , then the final image B is :

$$B = A + N \dots\dots\dots (3)$$

A and N are unrelated to each other [5].

The type of noise which is usually appears during image transmission is the salt-and-pepper noise. It is appears as black and/or white impulsive noise and its source either atmospheric or man-made (e.g. car engines) [6].

4. The Proposed Filter : An Adaptive Filter Using Rejection Test with F-distribution

The idea of the rejection test is employed to remove noise from images, when a pixel is expected to have an unusual value, the rejection test will be performed on that pixel to determine if it is really unusual or not.

This proposed filter is an adaptive filter of the type Decision Directed Filter. It is implemented on a 3×3 sliding window, where the pixels of this window shall be divided into two groups, the first one with the size $n_1=8$ includes all the window pixels excluding the Min or Max value, the second group is with the size $n_2=1$ and includes the Max or Min pixel in each time.

we can calculate the value of t^2 using equation (1) .With degree of freedom α we can obtain the value of F_7^1 from F-table and make a decision about the Max or Min value, whether it is unusual value or not, as shown below:

1. If $t^2 < F_7^1$ this means that the tested value is from the same population that the other value belongs to , in other words, it is not unusual value (it is not a noise pixel), so it shall not removed from the other pixels of the 3×3 window.
2. If $t^2 > F_7^1$ this means that the tested value is not from the same population that the other values belong to , in other words it is an unusual value (it is a noise pixel), so it must be removed from the other pixels of the 3×3 window.

The following points should be taken in consideration :

1. The reason beyond assuming that either the Max or Min value is the unusual value is that ; they are the most probable to be a noise pixel in the window (i.e. they are the most outliers pixels).
2. If the result of the rejection test show that the Max is an outlier, then the Min must not be tested as an outlier because there is no chance that a 3×3 window is corrupted by two noisy pixels.
3. If the result of the rejection test show that the Max is not an outlier, then the rejection test must be repeated again, assuming that the Min is the candidate outlier.

The above rejection test must be followed by the below decisions in order to replace the center of window by the average, median of the window, or leave it unchanged :

1. If the local standard deviation of the current window is equal to zero , that means the current area is "fairly constant" so the pixel

corresponding to the center of the window in the output image must be replaced with its corresponding pixel (with the center of the window), in other words , it will be left unchanged.

2. If the local standard deviation of the current window is less than a selected threshold , that means the current area is a *homogeneous* area (it contains no edge) so the pixel corresponding to the center of the window in the output image must be replaced with the *mean* (*average*) of the window.
3. If the local standard deviation of the current window is greater than a selected threshold , that means the current area is a *heterogeneous* area (it may contain an edge) so the pixel corresponding to the center of the window in the output image must be replaced with the *median* of the window; hence, edge will be preserved.

All of the above mean, median ,standard deviations are recalculated to the window after removing the noise from it by the rejection test (i.e. the window is clear from noisy pixels) , and this will reduce blurring of the image , as well as improve the edge preservation.

The Characteristic of This Filter

This proposed filter has the below characteristic :

1. This proposed method has more edge preservation and less blurring effects, because it replaces the pixel corresponding to the center of the window in the output image with the average or median of that window after removing the noisy pixels from the window under consideration.
2. This filter works perfectly well with salt and pepper noise and very well with Gaussian and uniform noise, and this is an advantage to this filter over other filters which work well with one type of noise and bad with other type .

Algorithm1 : An adaptive filter using rejection test with F- distribution

Input : Image corrupted by noise.

Output : Image clear from noise.

Step 1: - Create an output image g of dimension $M \times N$

- Select a threshold (standard deviation)
- Select α (the level of significant)
- Calculate p = the estimated ratio of the amount of noise pixels that corrupted the image.

Step 2: - For all pixel coordinate i and j do

- Select a 3×3 window of the current pixel and its 8-neighbour
- Sort the windows pixel grey level values in ascending order
- Let Max = the maximum value of the window and

Min = the minimum value.

Step 3: - Divide the pixels window into two groups , the first contains all the pixels excluding the Min, the second contains the Min pixel only.

\bar{x}_1 = average value of the first group , S_1^2 = variance for the first group.

\bar{x}_2 = Min (for the first iteration) or Max (for second iteration) ,
 $S_2^2 = 0$.

Step 4: - Calculate t^2 using equation (1) .

- From F table find the value of F_7^1 (degree of freedom 1 and $8-1=7$) , and with level of significant α .

- If $t^2 < F_7^1$ then // the tested pixel "Min" is not a noise Pixel

Recalculate the Mean, Sd , Median of the sliding window including the "Min".

Else

- If $t^2 > F_7^1$ then // the tested pixel "Min" is a noise pixel

window Mean = \bar{x}_1 ;

window $S_d = S_1^2$;

window Median = the Median excluding "Min" value;

Step 5: If ($p < 0.10$ and Min is a noise pixel) go to Step 6

Else

Go to Step 3 Repeating the above calculation assume that the pixel to be tested is the Max value of the current window.

Step 6: If $S = 0$ then Out-image [i][j] = In-image [i][j] .

Else

If $S < T$ then Out-image [i][j] = **Average** of the pixel grey level of the current window.

Else // it is an edge pixel

Out-image [i][j] = **Median** of the pixel grey levels of the current window

The above proposed statistical adaptive filters performed well against contaminated Gaussian or impulsive noise corruption cases. It do not require the priori knowledge noise statistics (such as σ^2) but only certain noise characteristic (noise estimation) which can easily be estimated . It adapts their behavior based on a local SNR measure , thus achieving edge preservation and noise smoothing in homogenous regions.

5. Evaluation Criteria

From the most commonly used evaluation criteria, three evaluation criteria have been used in this work. These criteria are used to measure the amount of error in the reconstructed (manipulated) image. The three evaluation measures are:-

1. The Root_Mean_Square_Error is computed by taking the square root of the squared error divided by the total number of pixels in the image.

$$Root_MSE = \sqrt{\frac{1}{N^2} \sum_{r=0}^{N-1} \sum_{c=0}^{N-1} [\hat{I}(r,c) - I(r,c)]^2} \dots\dots\dots(4)$$

Where $I(r,c)$ = the pixel brightness of the original image.

$\hat{I}(r,c)$ = the pixel brightness of the manipulated image.

N^2 = number of pixels in that image.

The smaller the value of the error metric, the better the reconstructed image represents the original image.

2. The SNR metrics consider the reconstructed image $\hat{I}(r,c)$ to be the signal and the error to be “noise”, the root_SNR is defined as:

$$Root_SNR = \sqrt{\frac{\sum_{r=0}^{N-1} \sum_{c=0}^{N-1} [\hat{I}(r,c)]^2}{\sum_{r=0}^{N-1} \sum_{c=0}^{N-1} [\hat{I}(r,c) - I(r,c)]^2}} \dots\dots\dots (5)$$

Where $I(r,c)$, $\hat{I}(r,c)$ as defined in equation (4).

With the signal to noise ratio (SNR) metrics, a larger number implies a better result.

3. The peak_SNR is defined as:

$$peak_SNR = 10 \log_{10} \frac{(L-1)^2}{\frac{1}{N^2} \sum_{r=0}^{N-1} \sum_{c=0}^{N-1} [\hat{I}(r,c) - I(r,c)]^2} \dots\dots\dots(6)$$

Where L is the number of gray levels (pixel brightness levels).

$I(r,c)$, $\hat{I}(r,c)$ as defined in equation (4).

In this measure a larger number implies a better result.

6. Results

The proposed method for noise removal has been tested over a number of images contaminated by different type of noise. The left hand side of figure (1) shows an image corrupted by Gaussian, uniform, and impulse noise respectively, while the right hand side of this figure shows the same images after applying the *Median* filter on those images. figure (2) shows the same contaminated images, while the right hand side of the figure shows those images after applying the proposed noise removal technique. It is clear that the traditional *Median* filter has the negative effect of blurring image edge and smearing image details, while the *proposed* filter is more edge and detail preservation.

Tables (1) and (2) show that the **time** required to removing noise from the test images using the proposed method is rather **slower** than that of the traditional methods. For example, to remove the noise of type uniform from a test image of size (640 × 480) it required 45.278 second, while the required time for the mean, median, and α -Trimmed Filter are 27.768, 29.983, 31.252 seconds respectively.

Tables (2), (3), and (4) show a number of fidelity criterion which are Root-MSE, SNR, and PSNR applied to the test images in figure (1) and (2) where the values of those criterion clearly show that the proposed method gives *much more accurate* results comparing to the traditional methods.

7. Conclusions

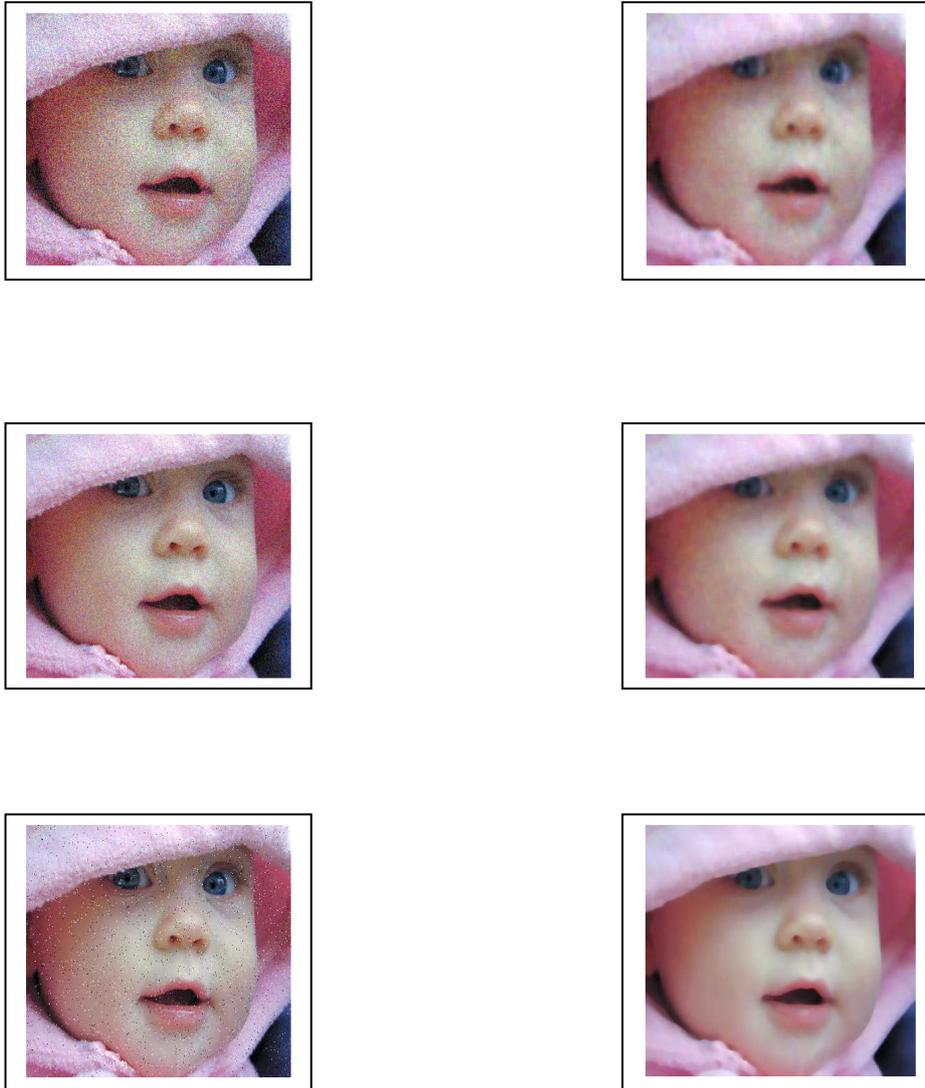
From the current research work, the following conclusions are derived.

1. The proposed statistical image noise removal adaptive filter has more *edge and details preservation* and less *blurring effects* (this is obvious from the images in figure (1) and figure (2)), besides they removes noise from edge areas as well as non-edges areas.
2. The proposed filter, adapt its behavior so that it *leaves* the non-noisy areas (fairly constant areas) *untouched*, while replacing the edge pixels (*heterogeneous areas*) by the *sliding window median* and the non edge pixel (*homogeneous areas*) by the *sliding window mean*, and this adaptation in its work lead to a very accurate results it gives (as table (3), (4) and (5) shows).

3. According to the fidelity criteria in table (3) , (4) and (5) , the proposed filter can remove noise of type **Gaussian**, **Uniforms** and **Salt and Pepper** very efficiently and it gives much more *accurate* results than the classical noise removal filters (i.e. mean, median and α -trimmed filter).
4. The proposed adaptive filter can be efficiently used with applications that required a very accurate processing (noise removing) , while it *not* required a very fast (close to real time) processing , because the proposed filter is rather slow as mentioned, hence , the proposed filter *can not* work with *video* noise removal properly , as well , it can work to remove noise from *static image* very accurately. .

References

- [1] Efford N., "Digital Image Processing", Addison Wesley, 2000.
- [2] Ilango G. , Marudhachalam R. , "New Hybrid Filtering Techniques For removal of Gaussian Noise From Medical Images", ARPN Journal of Engineering and Applied Sciences, Vol. 6 , No. 2, February 2011.
- [3] Jayaraj V. , Ebenezer D. Aiswarya K., " High Density Salt and Pepper Noise Removal in Images Using Improved Adaptive Statistics Estimation Filter", International Journal of Computer Science and Network Security, Vol. 9 No. 11, November 2009.
- [4] Kalavathy S. , " a Switching Weighted Adaptive Median Filter for Impulse Noise Removal", International Journal of Computer applications, Vol. 28 No. 9 , August 2011.
- [5] Parker J.R., "Algorithms for Image Processing and Computer Vision", John Wiley and Sons. 1997
- [6] Pitas I., "Digital Image Processing Algorithms and Applications", John Wiley and Sons, 2000.
- [7] Rahman M. M. , Ahmed F. , Jubair M. I. , " An Enhanced Non Linear Adaptive Filtering Technique for Removing High density Salt-and-Pepper Noise" , Vol. 38, No. 11, January 2012.
- [8] Senthilrajan A. , Ramaraj E., " High Density Noise Removal in Color Images Using Region of Interest Median controlled Adaptive Recursive weighted Filter", Proceeding of the International Multi Conference of Engineers and Computer Scientists , Vol. 2, March 2010.
- [9] Umbaugh S.E., "Computer Vision and Image Processing", Prentice Hall,1998.
- [10] Yamane T., " Statistics an Introductory Analysis ", Harper and Row Publishers, 1973.
- [11] Yazdi H. S. , Homayouni F. , " 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.



Figure(1) Left side : Images corrupted by Gaussian noise, Uniform Salt-and-pepper noise, noise ratio = 12.5 %

Right side : Images after performing Median filter



Figure(2) Left side : Images corrupted by Gaussian noise, Uniform Salt-and-pepper noise, noise ratio = 12.5 %

Right side : Images after performing the proposed filter

Table (1) : Computational speed statistics when applying a number of traditional , adaptive noise removal and the propose filter on an image corrupted by Uniform Noise.

Filter type	image size	Time require for noise removal
Mean	1024 × 768	58.992 second
Median	1024 × 768	63.343 second
α -Trimmed Filter	1024 × 768	68.342 second
Proposed Filter	1024 × 768	82.178 second

Table (2) : Computational speed statistics when applying a number of traditional , adaptive noise removal and the propose filter on an image corrupted by impulse Noise.

Filter type	image size	Time require for noise removal
Mean	640 × 480	27.768 second
Median	640 × 480	29.983 second
α -Trimmed Filter	640 × 480	31.252 second
Proposed Filter	640 × 480	45.278 second

Table (3) : The results of the evaluation criteria after applying the traditional filters and the proposed filter on an image corrupted by Gaussian noise.

Noise ratio = 12.5 %.

Criteria \ filter	Root_MSE	Root_SNR	Peak_SNR
Mean	17.274	7.365	23.382
Median	18.332	6.775	22.645
α -Trimmed Filter	16.759	7.675	23.645
Proposed Filter	4.892	12.987	33.872

Table (4) : The results of the evaluation criteria after applying the traditional filters and the proposed filter on an image corrupted by Uniform noise .

Noise ratio = 12.5 %.

Criteria \ filter	Root_MSE	Root_SNR	Peak_SNR
Mean	16.153	7.922	23.654
Median	15.106	8.564	24.547
α -Trimmed Filter	15,812	8.233	24,121
Proposed filter	4,623	13,827	34,918

Table (5): The results of the evaluation criteria after applying the traditional filters and the proposed filter on an image corrupted by Impulse noise (Salt and Pepper) .

Noise ratio = 12.5 % .

Criteria filter	Root_MSE	Root_SNR	Peak_SNR
Mean	17.254	7.354	23.392
Median	12.787	10.049	25.995
α -Trimmed Filter	15.722	8,873	24.225
Proposed Filter	3,871	14,124	35,921