A simple Cascade Method for Mixed Noise Removal.

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Abstract

Images are usually corrupted by type of noise called "mixed noise ", traditional methods do not give good results with the mixed noise (impulse with Gaussian noise) .In this paper a Simple Cascade Method (SCM) will be applied for mixed noise removal (Gaussian plus impulse noise) and compare it's performance with results that acquired when using the alpha trimmed mean filter and wavelet in separately. The performances are evaluated in terms of Mean Squane Error (MSE) and Peak Signal to Noise Ratio (PSNR).

Keywords: mixed noise, MSE, PSNR, SCM.

طريقة بسيطة لازالة الضوضاء المختلطة

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قسم هندسة الحاسبات والبرمجيات , كلية الهندسة ,الجامعة المستنصرية, بغداد ,العراق

الخلاصة

عادة الصور تعاني من تشوه عن طريق نوع من الضوضاء يسمى "الضوضاء المختلطة"، الأساليب التقليدية لا تعطي نتائج جيدة مع ضجيج مختلط (Impulse with Gaussian). في هذ ا البحث سيتم تطبيق أسلوب بسيط (SCM) لإزالة الضجيج المختلط وتقارن النتائج مع التي حصلت عند استخدام طريقة ألفا والمويجات في حدة. يتم تقييم الانجاز من خلال استخدام معياران لقياس نسبة الخطأ وهما MSE وPSNR.

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1. Introduction

The areas of application of digital image processing are so varied that some form of organization is desirable in attempting to capture the breadth of this field. One of the simplest ways to develop a basic understanding of the extent of image processing applications is to categorize images according to their source (e.g., visual, X-ray, and so on). The principal energy source for images in use today in the electromagnetic energy spectrum. Other important sources of energy include acoustic,

ultrasound, and electronic (in the form of electron beams used in electron microscopy). Synthetic images, used for modeling and visualization, are generated by computer and convert it into digital data form [1].

These datasets are contaminated with noise, either because of the data acquisition process, or because of naturally occurring phenomena. Pre-processing is the first step in analyzing such datasets. There are several different approaches to denoise images. The main problem faced during diagnosis is the noise introduced due to the consequence of the coherent nature of the image capture.

In image processing applications, linear filters tend to blur the edges and do not remove Gaussian and mixed Gaussian impulse noise effectively [2].

The original meaning of "noise" was and remains "unwanted sound"; By analogy unwanted electrical fluctuations themselves came to be known as "noise" [3]. In image processing applications, linear filters tend to blur the edges and do not remove Gaussian and mixed Gaussian impulse noise effectively [4].

Impulse noise is caused by malfunctioning pixels in camera sensors, faulty memory locations in hardware, or transmission in a noisy channel [5].

The presence of noise in images is a common phenomenon. The removal of noise from the image is a difficult task in the image processing [6]. Image noise is random (not present in the object imaged) variation of brightness or color information in images, and is usually an aspect of electronic noise. It can be produced by the sensor and circuitry of a scanner or camera. Image noise can also originate in film grain and in the unavoidable shot noise of an ideal photon detector. Image noise is an undesirable by-product of image capture that adds spurious and extraneous information.

The removal of high frequency impulsive noise by the use of median filters is widely accepted for image processing. As the median filters are nonlinear in character, they are better performers than any other filtering techniques in the removal of this type of noise. Nevertheless, conventional filters do not produce expected result with the increasing occurrence of probability error or with mixed noise (impulse with Gaussian noise) [6].

Gaussian noise is statistical noise that has its probability density function equal to that of the normal distribution, which is also known as the Gaussian distribution. In other words, the values that the noise can take on are Gaussian-distributed. A special case is white Gaussian noise, in which the values at any pairs of times are statistically independent (and uncorrelated).

2. Alpha-trimmed mean filter

It is windowed filter of nonlinear class; by its nature is hybrid of the mean and median filters. The basic idea behind filter is for any element of the signal (image) look at its neighborhood, discard the most typical elements and calculate mean value using the rest of them. The output this method can be formulated as follows [7]:

$$I(x,y) = (1/(rc-T_r))^* \Sigma\, h(r1,c1) \qquad (1)$$

Where h(r1,c1) represents the remaining elements , rc represents the window size the value of T_r represents the trim elements and can vary from 0 to (rc – 1),

2.1. Understanding alpha-trimmed mean filter

Now let us see, how to get alpha-trimmed mean value in practice. The basic idea here is to order elements; discard elements at the beginning and at the end of the got ordered set and then calculate average value using the rest.

For instance, let us calculate alpha-trimmed mean for the case, depicted in figure 1.

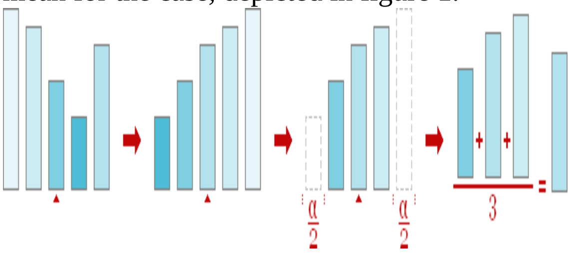


Figure 1- Alpha-trimmed mean calculation.

Thus, to get an alpha-trimmed mean, the element of the window should be ordered and then eliminate the elements at the beginning and at the end of the got sequenced collection and get average of the remaining elements. That is all — now alpha-trimmed mean calculated and signal, 1D in our case, filtered by alpha-trimmed mean filter. Let us make resume and write down step-by-step instructions for processing by alpha-trimmed mean filter.

2.2 Alpha-trimmed mean filter algorithm

1. Place a window over element
2. Pick up elements
3. Order elements
4. Discard elements at the beginning and at the end of the got ordered set
5. Take an average — sum up the remaining elements and divide the sum by their number.

A couple of words about alpha parameter responsible for trimmed elements. In practice alpha is the number of elements to be discarded, for instance, in our case alpha is two. Since our filter is symmetric one alpha is an even nonnegative number less than size of the filter window. Minimum value for alpha parameter is zero and in this case alpha-trimmed mean filter degenerates into mean filter. Maximum value for alpha is filter window size minus one and in this case filter degenerates into median filter [7].

3. Wavelet

Wavelet theory is applicable to several subjects. All wavelet transforms may be considered forms of time-frequency representation for continuous-time (analog) signals and so are related to harmonic analysis. Almost all practically useful discrete wavelet transforms use discrete-time filter banks. These filter banks are called the wavelet and scaling coefficients in wavelets nomenclature. These filter banks may contain either finite impulse response (FIR) or infinite impulse response (IIR) filters [7].

The wavelet representation of image such that let $\boldsymbol{f} = \{f_{ij}$, i, j = 1,2…M} denote the M ×M matrix of the original image to be recovered and M is some integer power of 2. During transmission the signal $\boldsymbol{f}$ is corrupted by independent and identically distributed (i.i.d) zero mean, white Gaussian Noise *nij* with standard deviation σ □i.e. $n_{ij} \sim N(0, \sigma^2)$ and at the receiver end, the noisy observations $g_{ij} = f_{ij} + \sigma$ □n_{ij} is obtained. The goal is to estimate the signal $\boldsymbol{f}$ from noisy observations g_{ij} such that Mean Squared error (MSE) is minimum. Let W and W^{-1} denote the two dimensional orthogonal discrete wavelet transform (DWT) matrix and its inverse respectively. Then Y = W.g represents the matrix of wavelet coefficients of *g* having four subbands (LL, LH, HL and HH). The sub-bands HH_k, HL_k, LH_k are called *details*, where k is the scale varying from 1, 2…… J and J is the total number of decompositions.

The size of the subband at scale k is $N/2^k \times N/2^k$. The subband LL_J is the low-resolution residue. The wavelet thresholding denoising method processes each coefficient of Y from the detail subbands with a soft threshold function to obtain X. The denoised estimate is inverse transformed to $F=W^{-1} X$ [8].

3.1 Discrete Wavelet Transform (DWT): A Brief Review

The wavelet transform has been extensively studied in the last decade. Many applications, such as compression, detection, and communications, of wavelet transforms have been found. There are many excellent tutorial books and papers on these topics. Here, we introduce the necessary concepts of the DWT. The basic idea in the DWT for a one dimensional signal is the following. A signal is split into two parts, usually high frequencies and low frequencies. The edge components of the signal are largely coefficient to the high frequency part. The low frequency part is split again into two parts of high and low frequencies. This process is continued an arbitrary number of times, which is usually determined by the application at hand. Furthermore, from these

DWT coefficients, the original signal can be reconstructed.

This reconstruction process is called the inverse DWT (IDWT). The DWT and IDWT can be mathematically stated as follows.
Let

$$H(\omega) = \sum_k h_k e^{-jk\omega}, \quad \text{and } G(\omega) = \sum_k g_k e^{-jk\omega}. \qquad (2)$$

be a lowpass and a highpass filter, respectively, which satisfy a certain condition for reconstruction to be stated later. A signal, x[n] can be decomposed recursively as

$$c_{j-1,k} = \sum_n h_{n-2k} c_{j,n} \qquad (3)$$

$$d_{j-1,k} = \sum_n g_{n-2k} c_{j,n} \qquad (4)$$

for j = J+1; J; …; J0 where $c_{J+1,k}$ = x[k], k∈Z, J+1 is the high resolution level index and J0 is the low resolution level index. The coefficients $c_{J0,k}$; $d_{J0,k}$; $d_{J0+1,k}$;….; $d_{J,k}$ are called the DWT of signal x[n], where $c_{J0,k}$ is the lowest resolution part of x[n] and $d_{j,k}$ are the details of x[n] at various bands of frequencies. Furthermore, the signal x[n] can be reconstructed from its DWT coefficients recursively

$$c_{j,n} = \sum_k h_{n-2k} c_{j-1,k} + \sum_k g_{n-2k} d_{j-1,k} \qquad (5)$$

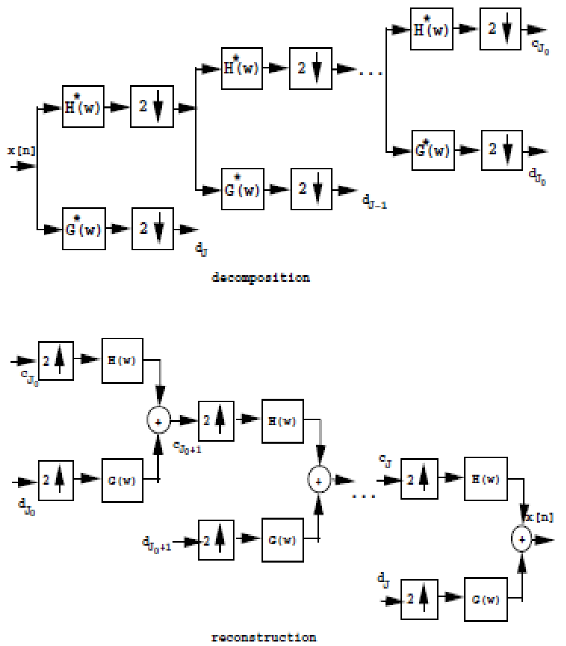


Figure 2- DWT for one dimensional signals.

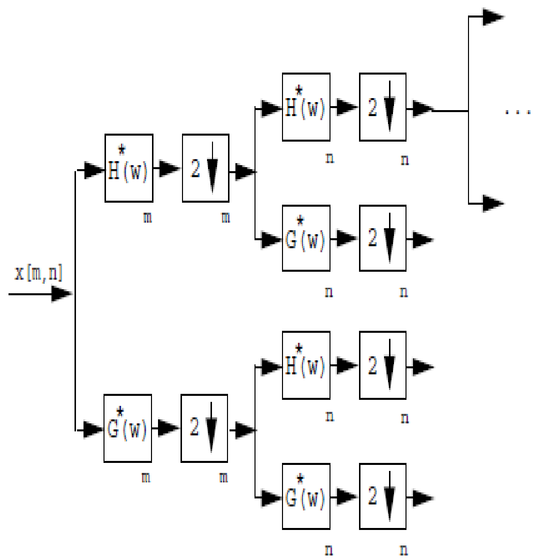


Figure 3- DWT for two dimensional images.

The above reconstruction is called the IDWT of x[n]. To ensure the above IDWT and DWT relationship, the following orthogonality condition on the filters H(w) and G(w) is needed:
abs(H(w)) + abs(G(w)) = 1
An example of such H(w) and G(w) is given by
$H(w) = 1/2 + 1/2\, e^{-jw}$
and
$G(w) = 1/2 - 1/2\, e^{-jw}$

which are known as the Haar wavelet filters. The above DWT and IDWT for a one dimensional signal x[n] can be also described in the form of two channel tree-structured filter banks as shown in figure 2. The DWT and IDWT for two dimensional images x[m; n] can be similarly defined by implementing the one dimensional DWT and IDWT for each dimension m and n separately. DWTn[DWTm[x[m; n]]], which is shown in figure 3. An image can be decomposed into a pyramid structure, shown in figure 4, with various band information: such as low-low frequency band, low-high frequency band, high-high frequency band etc. An example of such decomposition with two levels is shown in figure 4, where the edges appear in all bands except in the lowest frequency band, i.e., the corner part at the left and top [9].

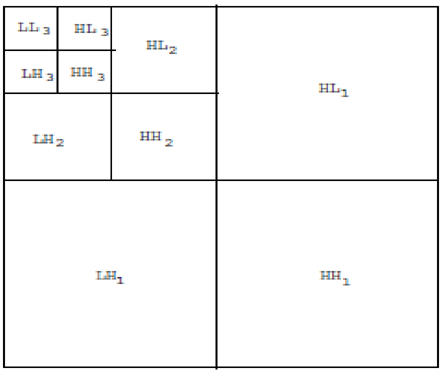


Figure 4- DWT pyramid decomposition of an image.

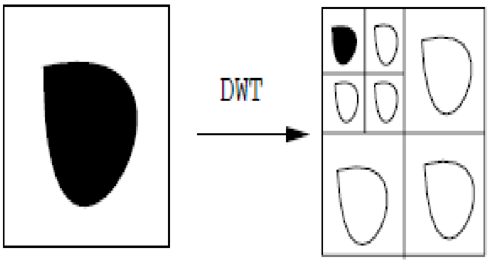


Figure 5 - Example of a DWT pyramid decomposition.

4. Measurement of Performance

To judge the performance of Image processing techniques for noise removal, MSE and PSNR are used.

4.1.MSE

Mean Squared Error is the average squared difference between a reference image and a distorted image. It is computed pixel-by-pixel by adding up the squared differences of all the pixels and dividing by the total pixel count.
For images A = {a1 .. aM} and B = {b1 .. bM}, where M is the number of pixels:

$$MSE(A,B) = 1/M \sum_{i=1}^{M} (a_i - b_i)^2 \quad (6)$$

The squaring of the differences dampens small differences between the 2 pixels but penalizes large ones.

4.2. PSNR

Peak Signal-to-Noise Ratio is the ratio between the reference signal and the distortion signal in an image, given in decibels. The higher PSNR, the closer the distorted image is to the original. In general, a higher PSNR value should correlate to a higher quality image, but tests have shown that this isn't always the case. However, PSNR is a popular quality metric because it's easy and fast to calculate while still giving reasonable results.
For images A = {a1 .. aM}, B = {b1 .. bM}, and MAX equal to the maximum possible pixel value (2^8 - 1 = 255 for 8-bit images)[10]:

$$PSNR(A,B) = 10 \log_{10}\left(\frac{MAX^2}{MSE(A,B)}\right) \quad (7)$$

5. A simple scheme for mixed noise removal

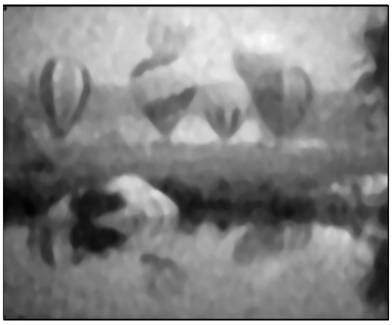
A new model is implemented for denoising images, firstly the alpha-trim filter implemented with different alpha value and with different window size ((3*3) and (5*5)) until get the best one with maximum PSNR and minimum MSE, this considered as an input to the wavelet, then this considered as an input to the alpha-trim also tested with deferent alpha factor value and with different window size ((3*3) and (5*5)) until got the best one. Seeing that with Table-1-, test1 and test3, SCM better than alpha-mean in its performance also in table 2 with (5*5) window, the SCM is the best in its performance, but when seeing in table 1, it has shown that the second test is not good but when got the best one in alpha-mean with 3*3 window size and considered as an input to the SCM with 5*5 window size, it gives a good result with MSE=.0035 which is less than that got it from alpha-mean method with(3*3)window size.

The performance of this scheme is compared with the wavelet denoising method and alpha-trim denoising method in separately.

Using MSE to evaluate the previously three methods, the experimental results show that the SCM method gives the minimum MSE.


-a-


-b-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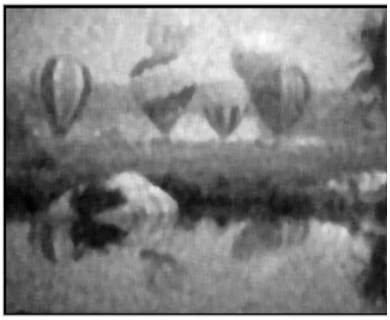
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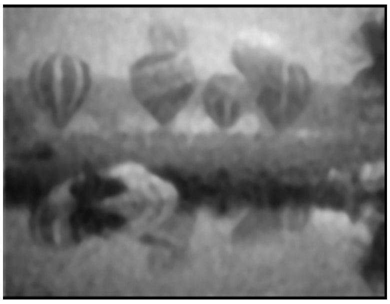
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Figure 6- Balloons image: a) the original image; b) the mixed noisy image; c)tested with alpha-mean, factor trim=4 , mse=.0163; d)tested with SCM with mse=0.0110 e) tested with SCM with mse=0.0055


-a-


-b-


-c-


-d-

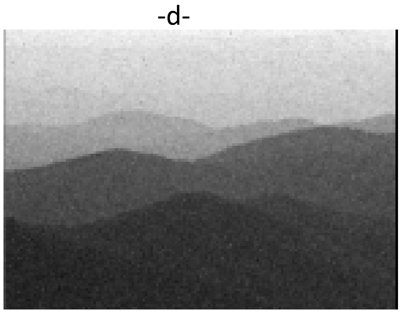
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Figure 7- Blue hills image: a) the original image; b) the mixed noisy image; c) tested with alpha-mean, Tr=4,mse=.0049; d) tested with SCM with Tr=4;mse=0.0039 e)tested with SCM with Tr=6; mse=0.0037

Table 1-The performance of the tested images in terms of MSE and PSNR

	(3*3) window size				
		Alpha-mean		scm	
	Tr	mse	psnr	mse	psnr
Test1	0	.0083	68.9174	.0058	70.5118
	2	.0069	69.7428	.0057	70.5667
	4	.0063	70.1449	.0056	70.6540
	6	.0062	70.1804	.0055	70.7523
	8	.0065	70.0001	.0055	70.7101
Test2	0	.0040	69.0446	2.3551	44.4107
	2	.0039	71.2517	3.9264	42.1909
	4	.0039	72.2517	7.1205	39.6057
	6	.0049	72.4051	18.0800	35.5588
	8	.0081	72.1647	148.0548	26.4266
Test3	0	.0188	65.3785	.0189	65.3562
	2	.0160	66.0933	.0160	66.0822
	4	.0147	66.4450	.0148	66.4374
	6	.0143	66.5680	.0143	66.5624
	8	.0146	66.4742	.0146	66.4751

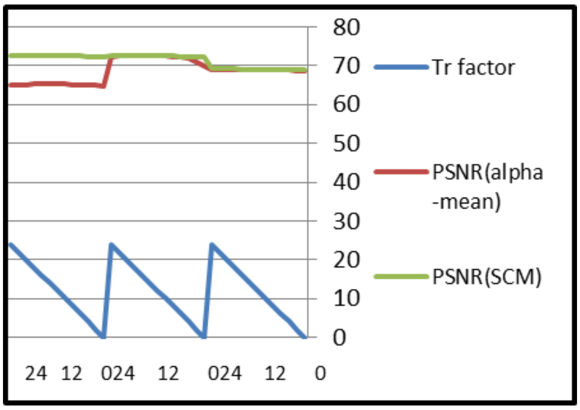

Figure 8- Performance result using PSNR

Table 2-The performance of the tested images in terms of MSE and PSNR

	(5*5) window size				
		Alpha-mean		scm	
	Tr	mse	psnr	mse	psnr
Test1	0	.0091	68.5496	.0082	68.9753
	2	.0086	68.7678	.0082	69.0031
	4	.0083	68.9454	.0081	69.0301
	6	.0081	69.0429	.0081	69.0564
	8	.0080	69.0742	.0080	69.0808
	10	.0080	69.0742	.0080	69.0999
	12	.0080	69.0742	.0080	69.1083
	14	.0080	69.0742	.0080	69.1173
	16	.0080	69.0742	.0079	69.1282
	18	.0080	69.0742	.0079	69.1422
	20	.0081	69.0607	.0079	69.1576
	22	.0081	69.0421	.0079	69.1527
	24	.0082	69.0141	.0079	69.1428
Test2	0	.0066	69.9168	.0038	72.3036
	2	.0052	71.0056	.0038	72.3396
	4	.0043	71.7859	.0038	72.3752
	6	.0039	72.2152	.0037	72.4113
	8	.0037	72.4139	.0037	72.4475
	10	.0037	72.5033	.0037	72.4813
	12	.0036	72.5411	.0036	72.5102
	14	.0036	72.5539	.0036	72.5454
	16	.0036	72.5502	.0036	72.5894
	18	.0036	72.5333	.0035	72.6436
	20	.0037	72.5057	.0035	72.6958
	22	.0037	72.4663	.0035	72.6929
	24	.0037	72.4073	.0035	72.6819
Test3	0	.0224	64.6379	.0039	72.2202
	2	.0212	64.8687	.0039	72.2202
	4	.0204	65.0296	.0038	72.3330
	6	.0200	65.1224	.0037	72.4488
	8	.0198	65.1728	.0037	72.4488
	10	.0196	65.1994	.0037	72.4488
	12	.0196	65.2127	.0037	72.4488
	14	.0196	65.2168	.0037	72.4488
	16	.0196	65.2117	.0037	72.4488
	18	.0197	65.1954	.0037	72.4488
	20	.0198	65.1636	.0037	72.4488
	22	.0200	65.1226	.0037	72.4488
	24	.0203	65.0528	.0037	72.4488

6. Conclusion

Three mixed noisy pictures are tested with the implementation with alpha-mean and SCM method , the proposed SCM is not only removed the mixed noise but also adjust the gray level to be nearest to the original one and with MSE less than that got from the implantation of alpha-mean method only. The performance of this method is evaluated through in terms of MSR and PSNR.

Reference

1. Gonzaliz R.C., **2009**, "Digital Image Processing.",p:53-56.
2. Satheesh S.,Prasad K., **2011**, “Medical Image Denoising using Adaptive Threshold based on Contourlet Transform,” Advanced Computing: An International Journal (ACIJ), Vol.2, No.2,pp:52-58.
3. Motwani M. C., Gadiya M. C., Motwani R. C.and Harris F.C., **2004**, "Survey of Image Denoising Techniques", Proc. of GSPx, Santa Clara Convention Center, Santa Clar, CA,pp: 27-30.
4. Charles Boncelet. **2005**, " Image Noise Models". In Alan C. Bovik. Handbook of Image and Video Processing. Academic Press. ISBN 0-12-11972-1.
5. A. Bovik, **2000**, "Handbook of Image and Video Processing", Academic Press.
6. Babak Nasersharif and Ahmed Akbari, **2004**,"Application of wavelet and wavelet thresholding in robust subband speech recognition".free wikpedia
7. Lakhwinder Kaur, Savita Gupta,R.C.Chuhan, **2002**,"image denoising using wavelet thresholding".
8. M. Vetterli and J. Kova_cevi_c, **1995**, Wavelets and Subband Coding, Prentice Hall, Englewood.
9. http://tdistler.com/iqa/algorithms.html