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Mixed Noise Reduction in Gray Scale Images Using Hybrid Filters Scheme

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Abstract:

An interactive algorithm to restoration of noisy image is presented in this paper. This algorithm composites of two filters working together with scalar recursive Kalman filter at same time. The first one is the arithmetic median filter with a suitable window length, while the second one is the mean filter with only five neighboring point, the output of these two filter are entered to a scalar Kalman filter, which process the image with raster scan. The suggested scheme is able to reduce the mixed noise(Additive Gaussian and Impulse) from the gray scale images. The output of the scalar Kalman filter is used to adjust (modify) the median and mean filters. Different examples are given, which illustrate the performance of the proposed algorithm comparing with the single mean, single Kalman, single median filter, and median- rational hybrid filter (MRHF) using two bidirectional median sub-filters.

ازالة الضوضاء المختلطة للصورة الرمادية باستخدام نظام المرشحات الهجينة

الملخص

في هذا البحث تم اقتراح خوارزمية تفاعلية لإعادة الصورة المشوشة. هذه الخوارزمية تتألف من مرشحين يعملان سوية مع مرشح Kalman المفرد في الوقت نفسه. هذين المرشحين هما مرشح median مع النافذة ذات طول مناسب ومرشح الأخر هو مرشح mean يتعامل مع خمس نقاط متجاورة من النافذة ذات طول محدد.
في المرحلة الأولى يتم إدخال الصورة المشوهة على كل من المرشح median والمرشح mean المعدل وإخراج هذين المرشحين يتم إدخالها على مرشح Kalman الذي يعالج الصورة بمسح raster. الخوارزمية المقترحة قادرة على تقليل mixed noise(Additive Gaussian and Impulse) من الصور التي هي من نوع gray scale. تم استخدام ناتج مرشح Kalman العددي لتعديل المرشحين median و mean. تم تقديم عدة أمثلة توضح أداء الخوارزمية المقترحة مقارنة مع مرشح median وحدة ومرشح mean وحدة ومرشح Kalman وحدة ومرشح median- rational hybrid filter (MRHF) using two bidirectional median sub-filters

Index Terms—mixed noise, additive noise, impulse noise, Kalman filter, median filter, mean filter.

I. Introduction

An image usually contains departures from the ideal signal that would be produced by general model of the signal production process. Such departures are referred to as noise. Noise arises as a result of un-modeled processes available on in the production and capture of the actual signal [1]. Digital images are often corrupted by different types of noise, namely, additive white Gaussian noise, impulse noise and mixed (Gaussian and impulse) noise. Noises are added in the image during acquisition by camera sensors and transmission in the channel. Hence, image denoising is one of the most common and important image processing operations in image and video processing applications [2].

There are many filters used to remove both Gaussian and impulse noise, or mixed noise. For example, Neha Jain [3] proposed a new, dynamic two-stage trilateral filter which has an efficiency of universal noise removal filter proposed by Garnett et al. [4] for denoising images corrupted with mixed noise. Neha Jain filter has an ability to detect impulse noise ratio in mixed noise and restore the corrupted pixel. Neha Jain [3] state during the text of his paper many approaches that are used to remove Gaussian and impulse noise as well as mixed Gaussian.

Two new and simple fuzzy filters named Fuzzy Tri –State filter, the Probor rule based fuzzy filter are proposed by S. Arukumart et al [5] to remove random valued impulse noise and Gaussian noise in digital gray scale and color images. The Fuzzy Tri– State filter is a non linear filter proposed for preserving the image details while effectively reducing both the types of noises. The Probor filter is sub divided into two sub filters. The first sub filter is responsible for quantifying the degree to which the pixel must be corrected using Euclidean distance[5].

In the present work, a simple algorithm is proposed to denoise images from mixed noise, in which two simultaneous operating filters (mean and median) are under laid with scalar Kalman filter.

The paper is organized as follows. Section II presents the model for Gaussian and impulse noise, section III briefly presents single scalar Kalman, which used simple model to represent the noisy image, with mixed noise. Section IV explained the operation the mean and the median filters, section V presents the proposed method. While section VI, and VII will include the simulation results and the conclusion.

II. MODEL FOR NOISE AND NOISY IMAGES

Fortunately, two noise models can adequately represent most noise added to images, Gaussian noise (additive) and impulse noise (multiplicative) [3, 4].

A. Additive Gaussian Noise

Gaussian noise is characterized by adding to each image pixel a value from a zero-mean Gaussian distribution. For the case of additive Gaussian noise, the noisy image *u*, is related to the original image u^0, by;

$$u_{i,j} = u^0_{i,j} + n_{i,j}$$

where each noise value *n* is drawn from a zero-mean Gaussian distribution.

B. Impulse Noise

In this type of noise, pixels in the image are very different in color and intensity from their surrounding pixels, the defining characteristic is that the value of noisy pixel bears no relation to the color of surrounding pixel. This is to notice that only a part of pixels is actually corrupted while others are kept noise free .To be precise, let $u^0_{i,j}$ and $u_{i,j}$ be the pixel values at location (*i*,*j*) in the original image and the noisy image, respectively. If the noise ratio is *p*, then

$u_{i,j} = n_{i,j}$ with probability *p* and

$u_{i,j} = u^0_{i,j}$

with probability (1-*p*)

Where $n_{i,j}$ is the gray-level value of the noisy pixel.

III. SINGLE SCALER KALMAN FILTER

The mathematical model for the original image and the noisy image (the observed image) with additive white Gaussian and impulse (salt and paper) noise can be expressed as follows:

Image model:

$$x(i, j) = \phi f(i, j) + w(i, j) \qquad \text{...(1)}$$

Observation model:

$$y(i, j) = x(i, j) + v_1(i, j) + v_2(i, j) \qquad \text{...(2)}$$

Where

ϕ State transition scalar.

$f(i,j)$ denotes the pixel at the i^{th} row and j^{th} column of the image.

w is the process additive white noise uncorrelated with v_1 and v_2 with mean zero and variance $Q(i,j)$.

v_1 is the additive white noise with mean zero and variance σ^2.

v_2 is the additive impulse noise with noise density D.

We, use the raster scan in implement the single Kalman filter or the proposed method (i.e., left to right, advanced one line, then repeat [6]). Thus at any point in the picture, some points will be the "past", one point will be the present, and the remaining points will be the "future". These words will thus have their conventional meaning with respect to the order in which the points are processed [6]. The recursive single Kalman filter for the model given in Eq.(1)&(2) is defined to be,

$$\hat{x}(i,j) = \phi\bar{x}(i,j-1) \quad \text{... (3)}$$

$$\hat{P}(i,j) = \phi\bar{P}(i,j-1)\phi^T + Q(i,j) \quad \text{... (4)}$$

$$K(i,j) = \hat{P}(i,j)[\hat{P}(i,j) + \sigma^2]^{-1} \quad \text{... (5)}$$

$$\bar{x}(i,j) = \hat{x}(i,j) + K(i,j)[y(i,j) - \hat{x}(i,j)] \quad \text{... (6)}$$

$$\bar{P}(i,j) = [1 - K(i,j)]\hat{P}(i,j) \quad \text{... (7)}$$

Where $\hat{x}(i,j)$ is the predicted state, $\hat{P}(i,j)$ is the predicted variance error, $K(i,j)$ is Kalman filter gain, $\bar{x}(i,j)$ is the restored pixel, and $\bar{P}(i,j)$ is associated with estimate errors of the corresponding items. The initial conditions are:

$$\bar{x}(1,1) = E[x(1,1)] = x(1,1)$$

$$\hat{P}(1,1) = \text{var}[x(1,1)]$$

IV. MEDIAN AND MEAN FILTERS

The operations of median and mean filter which are used in the proposed algorithm are explained in this section and as following;

- **MEDIAN FILTER**

The median filter is an alternative approach of the mean filter; this filter operates by calculating the median value within a specified neighborhood in an image and using this value in the output image. This is accomplished by sorting the pixel values inside the processing window from smallest to largest. Then, the middle value of the sorted list is selected as the output [7].

• MEAN FILTER:

The mean filter (or averaging filter) is a linear filter that operates on local groups of pixels called neighborhoods in the sliding window, and replaces the central pixel with an average of the pixels in this neighborhood. This can be done by applying the following equation [7]:

$$\hat{R}(i,j) = \frac{1}{N \times N} \sum_{x=i-\frac{N-1}{2}}^{i+\frac{N-1}{2}} \sum_{y=j-\frac{N-1}{2}}^{j+\frac{N-1}{2}} y(i,j) \qquad \ldots (8)$$

$N \times N$ is the size of the sliding window

$y(i,j)$ is the image pixel data within the window

$\hat{R}(i,j)$ is the output of the image at location (i,j)

V. THE HYBRID FILTERS SCHEMS(HFS)

In the present work, a Simple algorithm is proposed to denoise images, in which two simultaneous filters (mean and median) operating together with scalar Kalman filters are under laid. The first median filter is consider, furnishing the required observed information to the second kalman filter to estimate the noisy pixel as shown in Fig.(1). The operation for the proposed algorithm can be described by same Kalman filter equation but with some modifications:

(i) The median filter is used to obtain the predicted state of the Kalman filter $\hat{x}(i,j)$.

(ii) The mean filter is used to obtain the observer $y(i,j)=\hat{R}(i,j)$ that is needed to calculate the final state $\bar{x}(i,j)$.

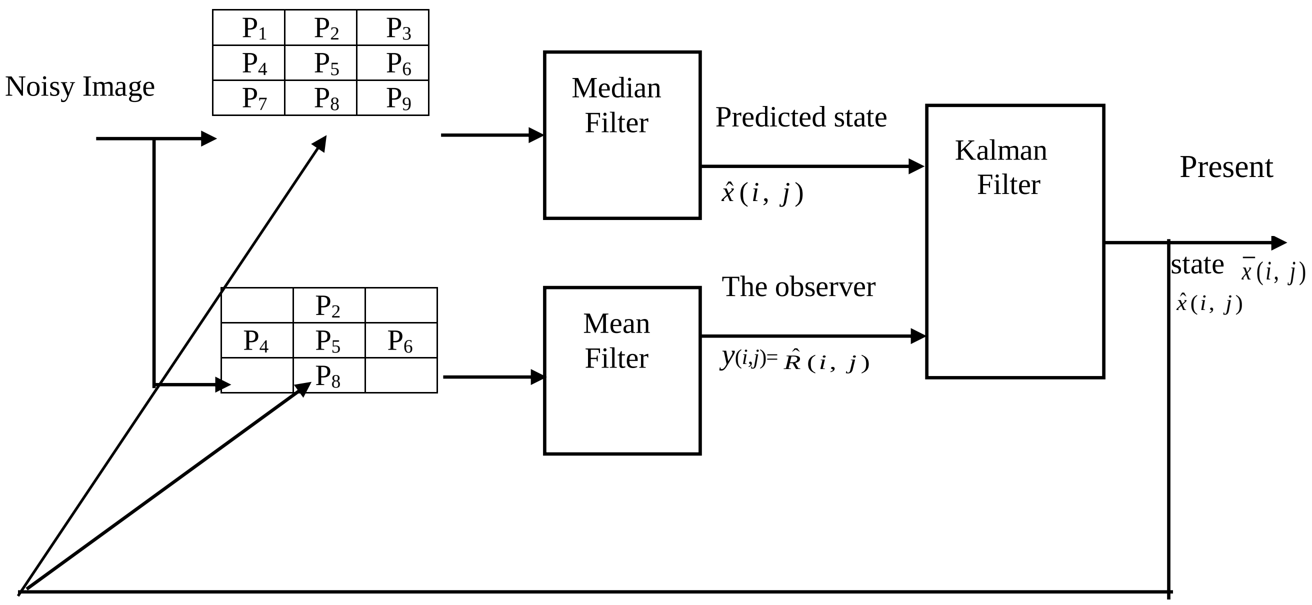

Fig.(1): the block diagram for the proposed algorithm.

The mean filter in the proposed algorithm has only five neighboring point, therefore, the $\hat{R}(i,j)$ becomes;

$$\hat{R}(i,j) = \frac{1}{5}[y(i,j) + y(i,j-1) + y(i,j+1) + y(i-1,j) + y(i+1,j)] \quad \ldots (9)$$

Now, if we assume $\phi = 1$, then, with the above modifications the Kalman filter equations becomes:

$$\hat{x}(i,j) = median \quad filter \quad output \quad \ldots(10)$$

$$\hat{P}(i,j) = \hat{P}(i,j-1) + Q(i,j) \quad \ldots(11)$$

$$K(i,j) = \hat{P}(i,j)[\hat{P}(i,j) + \sigma^2(i,j)]^{-1} \quad \ldots(12)$$

$$\bar{x}(i,j) = \hat{x}(i,j) + K(i,j)[\hat{R}(i,j) - \hat{x}(i,j)] \quad \ldots(13)$$

$$\hat{P}(i,j) = [1 - K(i,j)]P(i,j) \quad \ldots(14)$$

With

$Q(i,j) = \sigma^4$ and $\sigma^2(i,j)$ is the variance of $N\times N$(the size of the sliding window) of the noisy image $y(i,j)$, $\hat{P}(1,1) = \mathrm{var}(y(1,1)) = 0$

VI. SIMULATION RESULTS

Two images of different size are tests. The first one is, 400× 318 image of the " *kids* " as shown in Fig.(2-a), and the second one is 256× 256 image of the " *cameraman*" as shown in

Fig,(3-a). The original images and white Gaussian noise and impulse noise injected into to generate the corrupted images as shown in Fig.(2-b) and Fig.(3-b).

The signal -to noise ratio (SNR) for both corrupted images is calculated by [8];

$$SNR = 10 \log_{10} \frac{\sum x^2(i,j)}{\sum V^2(i,j)} \quad \ldots (15)$$

with $x(i,j)$ and $V(i,j)$ denoting the values of the original image and the observation noise respectively.
The single mean, single median filter, single scalar Kalman filter (SKF) with $Q(i,j)$ =0.01, and median-rational hybrid filter (MRHF)[9] using two bidirectional median sub-filters, in addition to the proposed algorithm used to denoise these images as shown in Fig.(2-c) to Fig.(2-g) for kids image, and Fig.(3-c) to Fig.(3-g) for cameraman image.
The signal-noise ratio of the restored images is computed as follows,[8],

$$SNR = 10 \log_{10} \frac{\sum x^2(i,j)}{\sum (x(i,j) - \bar{x}(i,j))^2} \quad \ldots (16)$$

where $\bar{x}(i,j)$ denotes the value of the restored images.

The denoising images can be also evaluated by the MSE [10],

$$MSE = \frac{1}{MN} \sum_{i=1}^{M} \sum_{j=1}^{N} (x(i,j) - \bar{x}(i,j))^2 \quad \ldots (17)$$

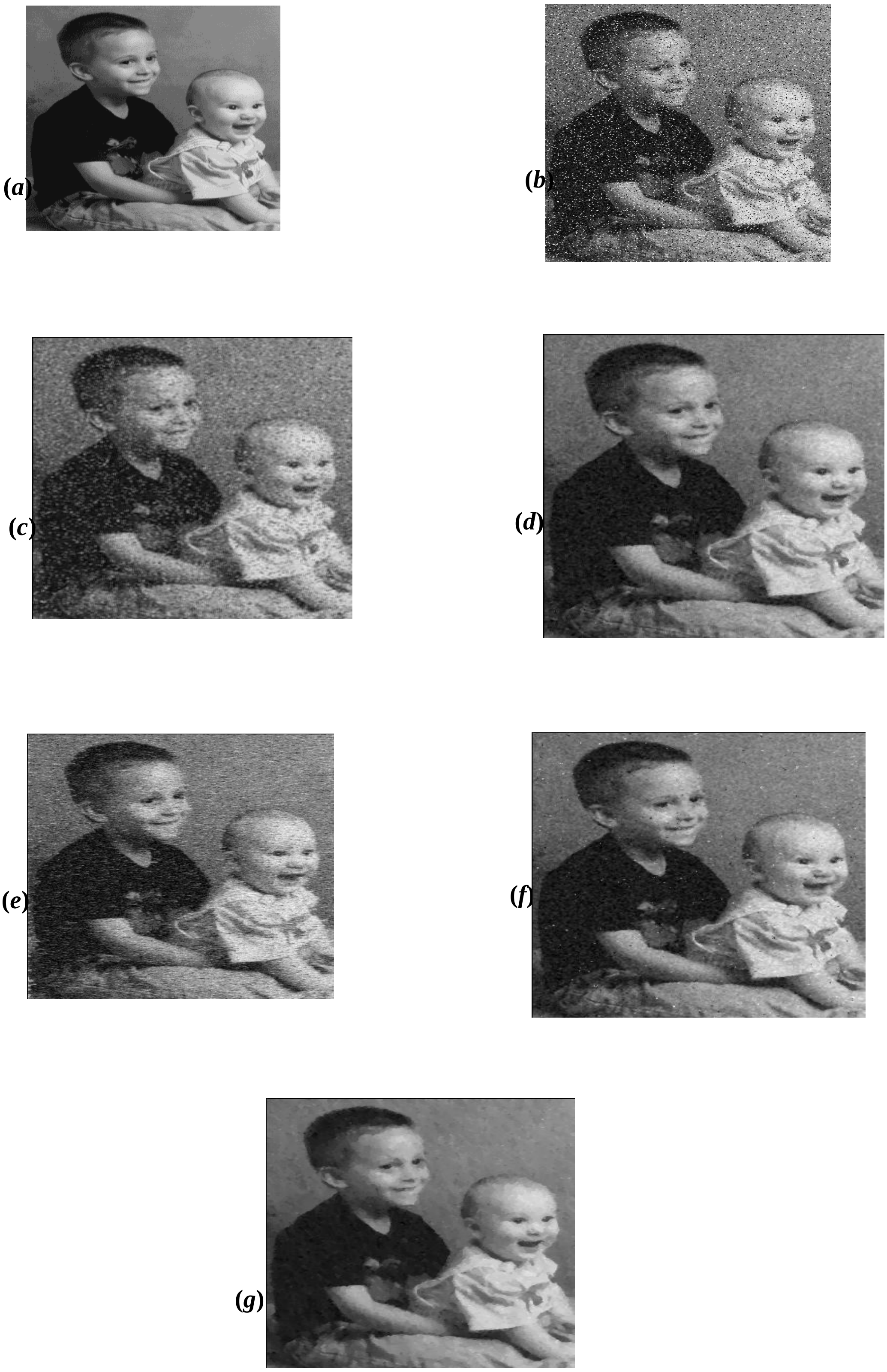

Fig.(2):a- the original image b-the noisy image with D=0.1 and v1=0.005 and SNR = 5.8898 db, c- image denoising by mean filter noise with SNR=16.0196db, d- image denoising by median filter with SNR=19.8574db, e- image denoising by Kalman filter with SNR=14.6439db, f- image denoising by median- rational hybrid filter (MRHF) using two bidirectional median sub-filters with SNR= 19.4549db, g- image denoising by hybrid Kalman filter with SNR= 21.0134db.

(*a*)

(*b*)

(*c*)

(*d*)

(*e*)

(*f*)

(*g*)

Fig.(3):a- the original image, b-the noisy image with D=0.01 and v1=0.01 with SNR = 12.5896 db, c- image denoising by mean filter with SNR=18.3461 db, d- image denoising by median filter with SNR=18.6346 db, e- image denoising by Kalman filter with SNR= 15.1509 db, f- image denoising by median- rational hybrid filter (MRHF) using two bidirectional median sub-filters with SNR= 19.1934 db, g- image denoising by hybrid Kalman filter with SNR= 18.9068 db.

Table(1) and Table(2) summarize the results of computer simulation to restore the kids image with impulse noise only with different density.

***Table(1):* the SNR for kids image with different filters and with only impulse noise at various density.**

Evaluation	**Image1: *kids* with Impulse noise only**					
	SNR ≅ "----"db					
Density D	Noisy image	MRHF	HFS	SKF	Mean	Median
0.05	11.39	**23.92**	22.84	18.70	18.75	22.76
0.2	5.45	17.83	**22.08**	13.04	13.5	20.48
0.6	0.67	5.6940	**13.77**	7.55	7.49	5.35
0.8	0.59	2.4423	**6.66**	5.67	5.69	1.16

***Table(2):* the MSE for kids image with different filters and with only impulse noise at various density.**

Evalu-ation	**Image1: *kids* with Impulse noise only**					
	MSE ≅ "----"					
Dens-ity D	Noisy image	MRHF	HFS	SKF	Mean	Median
0.05	0.0152	**0.0008**	0.0011	0.0459	0.0028	0.0011
0.2	0.0596	0.0034	**0.0013**	0.0106	0.0093	0.0019
0.6	0.1792	0.0563	**0.0088**	0.0364	0.0372	0.0609
0.8	0.2393	0.1190	**0.0451**	0.0571	0.0563	0.1599

Table(3) and Table(4) summarize the results of computer simulation to restore the kids image with only different Gaussian variance noise, while Table(5) and Table(6) summarize the results of computer simulation to restore this image with Gaussian(with different variance) and impulse noise(with different density).

***Table (3):* the SNR for kids image with different filters and with Gaussian noise at various variance.**

Evaluation	**Image1: *kids* with Gaussian noise only**					
	SNR ≅ "----"db					
Variance	Noisy image	MRHF	HFS	SKF	Mean	Median
0.05	7.123	13.70	**16.98**	12.73	15.55	13.75
0.2	2.85	8.7040	**13.20**	9.80	10.80	8.46
0.6	0.87	5.3757	**9.96**	7.80	7.47	4.78
0.8	0.487	4.7267	**8.93**	7.25	7.52	3.85

***Table(4):* the MSE for kids image with different filters and withGaussian noise at various variance.**

Evaluation	**Image1: *kids* with Gaussian noise only**					
	MSE ≅ "----"					
Variance	Noisy image	MRHF	HFS	SKF	Mean	Median
0.05	0.0405	0.0089	**0.0042**	0.0111	0.0058	0.0088
0.2	0.1085	0.0282	**0.0100**	0.0219	0.0174	0.0298
0.6	0.1710	0.0606	**0.0211**	0.0347	0.0322	0.0695
0.8	0.1867	0.0703	**0.0267**	0.0394	0.0374	0.0860

Table(5): ***the SNR for the kids image with different filters and with Gaussian and impulse noise.***

Evaluation		**Image1: *kids* with mixed (Gaussian and Impulse) noise**					
		SNR≅ "----"db					
Var.	den. D	Noisy image	MRHF	HFS	SKF	Mean	Median
0.01	0.01	12.27	19.10	**20.35**	16.29	19.46	18.91
0.1	0.1	3.52	10.06	**14.34**	10.42	11.55	10.05
0.5	0.1	0.75	5.27	**9.66**	7.64	7.88	4.53
0.1	0.5	-2.38	5.05	**10.07**	7.39	7.42	4.37

Table(6): ***the MSE for the kids image with different filters and with Gaussian and impulse noise.***

Evaluation		**Image1: *kids* with mixed (Gaussian and Impulse) noise**					
		MSE≅ "----"					
Var.	den. D	Noisy image	MRHF	HFS	SKF	Mean	Median
0.01	0.01	0.0124	0.0026	**0.0019**	0.0049	0.0024	0.0027
0.1	0.1	0.0929	0.0206	**0.0077**	0.0190	0.0146	0.0206
0.5	0.1	0.1758	0.0621	**0.0226**	0.0359	0.0341	0.0736
0.1	0.5	0.3612	0.0653	**0.0206**	0.0381	0.0379	0.0764

In other word, the results of computer simulation to restore the cameraman image with impulse noise which has a different density are summarize in Table(7) and Table(8). Table(9) and Table(10) summarize the results of restored this image with Gaussian noise with different variance only, while Table(11) and Table(12) summarize the results of computer simulation to restore the this image which corrupted with Gaussian noise(with different variance) and impulse noise(with different density D).

Table(7): the SNR for cameraman image with different filters with impulse noise only at various density.

Evaluation	**Image2:Cameraman with Impulse noise only**					
	SNR ≅ "----"db					
Density D	Noisy image	MRHF	HFS	SKF	Mean	Median
0.01	19.01	**23.77**	20.55	17.90	19.84	21.61
0.1	9.58	**21.41**	20.11	14.58	16.22	20.78
0.5	2.44	8.67	**14.73**	8.81	9.06	8.78
0.7	1.034	4.82	**9.90**	7.05	7.22	3.99

Table(8): the MSE for cameraman image with different filters with impulse noise only at various density.

Evaluation	**Image2:Cameraman with Impulse noise only**					
	MSE ≅ "----"					
Density D	Noisy image	MRHF	HFS	SKF	Mean	Median
0.01	0.0028	**0.0011**	0.0024	0.0044	0.0028	0.0019
0.1	0.0299	**0.002**	0.0027	0.0097	0.0065	0.0023
0.5	0.1551	0.0369	**0.0091**	0.0355	0.0338	0.0360
0.7	0.2141	0.0895	**0.0278**	0.0533	0.0515	0.1085

***Table(9)*: the SNR for cameraman image with different filters with Gaussian noise at various variance.**

Evaluation	**Image2:Cameraman with Gaussian noise only**					
	SNR ≅ "----"db					
Variance	Noisy image	MRHF	HFS	SKF	Mean	Median
0.01	17.42	**19.38**	19.10	15.33	18.81	18.74
0.1	7.416	11.98	**14.88**	11.95	13.34	11.98
0.5	1.76	6.85	**10.73**	8.50	8.99	6.23
0.7	0.96	6.06	**9.48**	7.95	8.24	5.17

***Table(10)*: the MSE for cameraman image with different filters with Gaussian noise at various variance.**

Evaluation	**Image2:Cameraman with Gaussian noise only**					
	MSE ≅ "----"					
Variance	Noisy image	MRHF	HFS	SKF	Mean	Median
0.01	0.0049	**0.0031**	0.0033	0.0079	0.0036	0.0049
0.1	0.0492	0.0172	**0.0088**	0.0202	0.0126	0.0492
0.5	0.1811	0.0561	**0.023**	0.0398	0.0344	0.1811
0.7	0.22	0.0673	**0.031**	0.0435	0.0408	0.22

Table(11): the SNR for the cameraman image with different filters and with Gaussian and impulse noise.

Evaluation		**Image2:Cameraman with mixed (Gaussian and Impulse) noise**					
		SNR ≅ "----"db					
Var.	den. D	Noisy image	MRHF	HFS	SKF	Mean	Median
0.01	0.01	13.55	**19.31**	18.89	15.10	18.32	18.65
0.1	0.1	4.68	11.04	**14.21**	10.58	11.94	11
0.5	0.1	0.73	6.26	**9.46**	8.06	7.81	4.45
0.1	0.5	0.53	5.94	**10.07**	7.82	7.42	4.37

Table(12): the MSE for the cameraman image with different filters and with Gaussian and impulse noise.

Evaluation		**Image2:Cameraman with mixed (Gaussian and Impulse) noise**					
		MSE ≅ "----"					
Var.	den. D	Noisy image	MRHF	HFS	SKF	Mean	Median
0.01	0.01	0.0120	**0.0032**	0.0035	0.0083	0.0040	0.0037
0.1	0.1	0.1078	0.0925	**0.0103**	0.0238	0.0174	0.0216
0.5	0.1	0.1768	0.0643	**0.0237**	0.0418	0.0346	0.0750
0.1	0.5	0.1851	0.0692	**0.0206**	0.0459	0.0379	0.0764

The efficacy of the proposed HFS algorithm can easily be verified from the results and the above twelve tables, especially at very high mixed noise.

VII. CONCLUSIONS

a simple hybrid filters scheme was introduced as a new approach to image restoration from mixed noise. This scheme consists from three filter working together at the same time. The first one is median filter with 3×3 window length, this filter will provide the observer signal to the scalar Kalman filter (SKF), the second filter is the mean filter which consider as a predicted state to the Kalman filter. The output of the Kalman filter will be used to update the center pixel of mean and median filter window. Computer simulations with two different images show that the proposed scheme is more efficient than the mean, median, median-rational hybrid filter (MRHF) using two bidirectional median sub-filters, and single Kalman filter. For future, we suggest use the proposed approach to restore the color images that are corrupted by mixed noise.

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