Multi-Channel Image Noise Filter based on PCNN

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***Abstract*—Through analysis of PCNN's work principle, a noval filtering approach capable of detecting and removing impulsive noise in multi-channel images. The filter detects noise pixels in the image by utilizing PCNN's specific feature that the fire of one neuron can capture firing of its adjacent neurons due to their spatial proximity and intensity similarity. Then it estimates the noise pixels by a VMF-likely vector filtering. Experimental results show that the proposed filter has excellent performance, and is able to preserve fine details while suppressing impulsive noise.**

***Index Terms*—Multi-channel image processing, Nonlinear vector filtering, PCNN**

I. INTRODUCTION

The perception of color is important to vision system of humans and machines, since they use color information to sense the environment and recognize the objects on the scene. Because the acquisition or transmission of digital images through sensors or communication channels is often affected by impulsive noise [1-4] (e.g., bit errors [5] or mixed impulsive and Gaussian noise [2,5]), the aim of pre-processing techniques is the noise filtering [5,6,7] which enables communication in noisy environments [5] and processing of different kinds of multi-channel images (e.g., enhancement of cDNA microarray images [8,9], digitized artwork images [10,11], old movies [12-14], and images acquired by sensors [15,16]).

The purpose of the image filtering is the removal of useless information such as various signal distortions in order to obtain the image which corresponds as closely as possible to the output of an ideal imaging system [1]. In many applications, it is indispensable to remove the corrupted pixels to continue subsequent image processing operations such as edge detection, image segmentation, and pattern recognition. To convey the desired information correctly, the noisy signal should be processed by a filtering algorithm which removes the noise, but retains the image structure.

Many of the methods used for multi-channel image noise reduction such as componentwise (marginal) median filters [17, 18] are direct extensions of the methods used for gray-scale imaging. The independent processing of color image channels is, however, inappropriate and leads to strong color artifacts (sub-optimal estimates in sense of color information), which are caused by scalar ordering of the multi-channel samples in the input of the filter. To overcome this problem and avoid the color artifacts produced by marginal approaches, the vector processing of color image data as vector fields is desirable due to the strong correlation that exists among the image channels [19-22]. Therefore, the standard techniques developed for monochrome images have to be extended in a way which exploits the correlation among the image channels and processes the input multi-channel samples as the set of image vectors.

In the case of impulsive noise, (e.g., bit errors and outliers), filtering approaches based on the order-statistics theory are often employed [5, 7, 23, 24]. These nonlinear filters: (i) operate by ordering the image samples inside a processing window, (ii) are able to match the underlying statistical model, and (iii) they are computationally simple. In gray-scale images, the ordering of the samples inside the filter window moves the atypical image samples, often corrupted by noise, to the borders of the ordered set. Therefore, the middle-positioned samples in the ordered sequence represent the robust estimates in the environments corrupted by outliers.

It has been widely recognized [19-22] that the nonlinear vector processing of color images is the most effective way to filter out outliers. For that reason, a number of filtering approaches, such as those presented in [25-27], have been developed to extend the filtering efficiency of the standard filtering approaches. Vector median filter [19] is a typical example of such an extension, when the median defined over the gray-scale samples has been replaced with the lowest ranked multi-channel sample achieved by vector ordering [1]. This filter is very often used for the removal of impulsive

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noise in color images. On the other hand, the standard median filter [23] or its multi-channel extensions, i.e., the vector median filter [19] and the basic vector directional filter [21], are unable to adapt their behavior to varying noise and signal statistics related to the local image information of the samples inside a sliding filtering window. These filters performing the fixed amount of smoothing result in blurring of fine image details.

In the late 1980s, Eckhorn et al. discovered that the midbrain in an oscillating way created binary images that could extract different features from the visual impression when they had studied the cat visual cortex [36-39]. Based on these binary images the actual image is created in the cat brain. Due to this discovery they developed a neural network, called Eckhorn's model, to simulate this behavior. In the early 1990s, Rybak et al. also found the similar neural behavior based on the study of the visual cortex of the guinea pig and developed a neural network, called Rybak's model [39,40]. Because Eckhorn's model and Rybak' model provided a simple, effective way for studying synchronous pulse dynamics in networks, they was recognized as being very potential in image processing [41-43].

The above discoveries have paved the way for the generation of pulse-coupled neural network. Then Johnson et al. carried on a number of modifications and variations to improve its performance as image processing algorithms [41, 42]. This modified neural model is called pulse-coupled neural networks (PCNN).

The PCNN is a single layer, two-dimensional, laterally connected network of integrate-and-fire neurons, with a 1:1 correspondence between the image pixels and network neurons. This is a neural network that without any training needed. The output images at different iterations typically represent some segments or edges information of the input image. As a new generation of neural network, the PCNN is good at digital image processing and applied in many fields like image segmentation, image enhancement, image fusion, object and edge detection, pattern recognition, etc [48].

The rest of this paper is organized as follows. In Section 2, a brief overview of the PCNN model is presented. In Section 3, we propose a new color image filter based on PCNN. In Section 4, the proposed method is tested compare with some existing filters. Section 5 is the conclusion and this paper end with acknowledgements in Section 6.

II. PCNN MODEL

As mentioned above, the PCNN is two-dimensional, single layered, laterally connected neural network of pulse-coupled neurons, which connect with image pixels one to one. Because each image pixel is associated with a neuron of the PCNN, processing the pixels can be translated into processing the corresponding neurons of the PCNN.

The PCNN neuron's structure is shown in Fig. 1. The neuron consists of an input part, linking part and a pulse generator. The neuron receives the input signals from feeding and linking inputs. Feeding input is the primary input from the neuron's receptive area. The neuron receptive area consists of the neighboring pixels of corresponding pixel in the input image. Linking input is the secondary input of lateral connections with neighboring neurons. The difference between these inputs is that the feeding connections have a slower characteristic response time constant than the linking connections. The standard PCNN model is described as iteration by the following equations:

$$F_{ij}[n] = e^{-\alpha_F} F[n-1] + V_F \sum_{kl} w_{ijkl} Y_{ij}[n-1] + I_{ij} \tag{1}$$

$$L_{ij}[n] = e^{-\alpha_L} L_{ij}[n-1] + V_L \sum_{kl} m_{ijkl} Y_{ij}[n-1] \tag{2}$$

$$U_{ij}[n] = F_{ij}[n](1 + \beta L_{ij}[n]) \tag{3}$$

$$Y_{ij}[n] = step(U_{ij}[n] - E_{ij}[n-1]) \tag{4}$$

$$E_{ij}[n] = e^{-\alpha_E} E_{ij}[n-1] + V_E Y_{ij}[n] \tag{5}$$

In these equations, I_{ij} is the input stimulus such as the normalized gray level of image pixels in (i,j) position, $F_{ij}[n]$ is the feedback input of the neuron in (i,j), and $L_{ij}[n]$ is the linking item. $U_{ij}[n]$ is the internal activity of neuron, and $E_{ij}[n]$ is the dynamic threshold. $Y_{ij}[n]$ stands for the pulse output of neuron and it gets either the binary value 0 or 1. The input stimulus (the pixel intensity) is received by the feeding element and the internal activation element combines the feeding element with the linking element. The value of internal activation element is compared with a dynamic threshold that gradually decreases at iteration. The internal activation element accumulates the signals until it surpasses the dynamic threshold and then fires the output element and the dynamic threshold increases simultaneously strongly [47]. The output of the neuron is then iteratively fed back to the element with a delay of one iteration.

The inter-connections M and W are the constant synaptic weight matrices for the feeding and the linking inputs, respectively, which dependant on the distance between neurons. Generally, M and W (normally W=M) refer to the Gaussian weight functions with the distance. β is the linking coefficient. α_F, α_L and α_E are the attenuation time constants of $F_{ij}[n]$, $L_{ij}[n]$ and $E_{ij}[n]$, respectively. V_F, V_L and V_E denote the inherent voltage potential of $F_{ij}[n]$, $L_{ij}[n]$ and $E_{ij}[n]$, respectively.

Clearly, the standard PCNN has many parameters. A good algorithm using PCNN can make each parameter perform its own functions and further finish the task of data processing very well. Hence, we give a brief explanation about the functions of these parameters in the following.

For the feeding channel, α_F determines the rate of decay of the feeding channel. Bigger α_F causes faster decay of the feeding channel. V_F can enlarge or reduce the influence from surrounding neurons. Matrix W refers to the mode of inter-connection among neurons in the feeding receptive field. Generally, the size of W denotes the size of the feeding receptive field. The value of matrix element w_{ijkl} determines the synaptic weight strength. In most cases, this channel is simplified via α_F=0 and V_F=0.

Different from the feeding channel, the link channel usually keep itself as it is. The link channel also has three

parameters (α_L, V_L and M) that have the same function to the parameters (α_F, V_F and W), respectively. It is noteworthy that the mode of inter-connection should be designed carefully according to the task of data processing (e.g. image denoising), for it has a great effect on the output of PCNN. Usually, the inter-connection employs the Gaussian weight functions with the distance.

The linking coefficient β is an important parameter, because it can vary the weighting of the linking channel in the internal activity. Hence, its value is usually depended on different demands. For example, if much influence from the linking channel is expected, β should be given larger value. All neurons often have the same value of β. It is not absolute. Each neuron can have its own value of β.

For the pulse generator, α_E indicates the rate of decay of the threshold in the iterative process. Because it directly decides the firing time of neuron, α_E is a significant parameter. Smaller α_E can make the PCNN work in a meticulous way but it will take much time to finish the processing. On the contrary, larger α_E can decrease more running time of PCNN. V_E decides the threshold value of fired neuron. If expecting that neuron just fires one time, α_E should be set a large value.

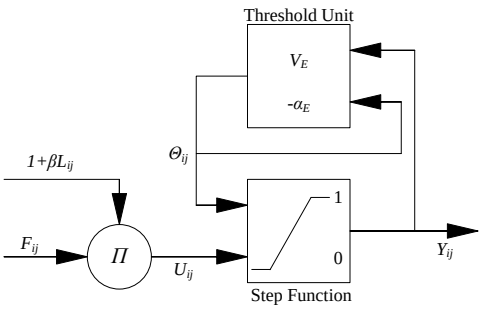


Fig 1. PCNN model.

III. PROPOSED FRAMEWORK

A. Basic idea

In case of impulsive noise, color image noise pixels corrupted each channel of the image independently [19-22]. Each channel has been corrupted in different positions, but they are all corrupted in the same characteristic and pattern. Impulsive noise is a very interested noise: in each channel of the image, the value of the corrupted pixel is quite different from the pixels that have not been affected nearby, which means that the neurons corresponding to the noise pixels will not fire synchronously with the neurons that have not been affected nearby. Thus the basic idea we adopting PCNN for noise detection and removal is to fix the stimulus of noise pixels to make them fire with the normal pixels synchronously.

Color image is a multi-channel image which is not likely a gray image. For a gray image, we can build a PCNN which neurons are one by one corresponding to each pixel in the image. If we use PCNN for each channel separately and then combine the filtered channels together, because of each channel is affected in different place, unexpected new color will be introduced to the image and hue will change in the original noise pixels. To solve this problem, we have to translate the image from original R, G, B three channels into a new space which can amplify the difference between noise pixels with normal pixels.

Thus we proposed a noise detection and removal filter based on PCNN which only modify the noise pixels in the new space. The filter only operate a neuron (i, j) when it fires, the algorithm is implemented in the following steps:

(1) When neuron (i, j) fires within its nearby neurons already fired, it means that this neuron is not able to be captured to fire because of its nearby neurons firing, so the corresponding pixel is a noise pixel, and because its fire time is later than the nearby neurons, so this pixel is darker than supposed normal value. It needs to be set brighter.

(2) When neuron (i, j) fires with its nearby neurons do not fire yet, it means that this neuron's firing can not capture its nearby neurons firing, so the corresponding pixel is a noise pixel, and because its fire time is earlier than the nearby neuron, so this pixel is brighter than supposed normal value. It needs to be set darker.

(3) When neuron (i, j) fires with half of the nearby neurons already fired and half not fire yet, it means that this neuron is not a noise pixel, it should remains unchanged.

(4) After this action, the algorithm will get a list of suspicious noise pixels in the image. For each noise pixel, we employ a VMF-likely algorithm for filtering: build a processing window which central point is the noise pixel, then use VMF for the pixels in the processing window expects the pixels in the suspicious noise pixels list to select the median value to replace the central pixel.

B. Noise pixel detection

RGB color space is setup from primary color spectrum, it is quite suitable for hardware implementation, but not good for explanation in human vision system. In RGB color space, impulsive noise corrupts one or more channels, the probability of corruption in each channel is equal. So if we detect noise directly in RGB color space, we should consider the corruption situation in three channel equally, and the output image also can not fix the characteristic of human vision system. Human vision system use hue, saturation and intensity to describe color and observe colorful objects. In HSI color space, Impulsive noise corruption focus more on intensity than hue and saturation. The following equations can translate image from RGB space to HSI space:

$$H = \begin{cases} \theta & , B \le G \\ 2\pi - \theta & , B > G \end{cases} , \quad \theta = \arccos\left(\frac{2 \times R - G - B}{2 \times ((R-G)^2 + (R-B)(G-B))^{1/2}} \right) \tag{6}$$

$$S = 1 - 3 \times \min(R, G, B) / (R + B + G) \tag{7}$$

$$I = (R + G + B) / 3 \tag{8}$$

If the image is filtered in H, S, I channel separately, new color will be introduced to the image, and details and edges will also be destroyed. Thus we construct m:

$$m = (\eta + \cos H)^p S^q I^{(1-p-q)} , \ \eta \ge 2, p \ge 0, q \ge 0, p + q \le 1 \tag{9}$$

By constructing *m*, we amplify the difference between noise pixel and its nearby pixels, and consider affection to hue, saturation and intensity by the noise pixel. Thus we avoided the problem of handling the noise in one or more channels separately. Use this equation for every pixel in the image, we will get a matrix $M = \{m_1, m_2, ..., m_n\}$ which has same size as the image. To detect the noise pixel, we use *M* to active a PCNN which has the same size of *M*. Let the neuron network runs to have all the neurons fired. And record the firing moment of each neuron to the Firing Time Map *(FTM*). For each pixel m_i in *M*, check the slide window which has this pixel as central point, remark the total pixel amount in the window as S_0, remark the amount of pixel firing before central point as S_1, remark the amount of pixel firing after central point as S_2, if $S_1>S_0/2$ or $S_2>S_0/2$ then the central point is corrupted by noise, otherwise it is not corrupted.

C. Noise pixel removal

If the pixel is not corrupted, leave it unchanged. If the pixel is corrupted, we proposed an auto parameter a VMF likely algorithm: setup a processing window which has the corrupted pixel as central point, if over half of the pixels in the window fire time are earlier than central point ($S_1>S_0/2$), choose the pixels in this processing window to build $\Gamma = \{x_1, x_2, ..., x_L\}$, if x_l and x_k are two pixels in Γ, the Euclidean distance $D(l,k)$ is: $D(l,k) = \|x_l - x_k\|_2$, then set central point as $\arg\min_{x_k \in \Gamma}\left[\sum_{l=1}^{L} D(l,k)\right]$. If over half pixels in the window fire later than central point($S_2>S_0/2$), then choose the pixels in this processing window and are not in the noise pixel list to execute the above operations. By using this method, we can remove noise without affect image details and edges, and avoid disturbance from other noise pixel. The algorithm working flow is shown in Figure 2.

The parameters' value should consider the following points: (1) To make neurons in PCNN fire quickly because of E_{ij}'s value rise rapidly, V_E should be rather bigger; (2) For neuron connect with its nearby neurons, and locate noise point, the linking coefficient β should be bigger; (3) to set m's value, η is used to smooth effect of hue. Set value of p, q should consider impulsive affection on image focus on intensity and hue. In the experiments of next section, the parameters' values are set as following: β=0.27, α_E =0.2, V_E =350, $w = \begin{bmatrix} 0.2 & 1 & 0.2 \\ 1 & 0 & 1 \\ 0.2 & 1 & 0.2 \end{bmatrix}$; η=2, p=0.5, q=0.1.

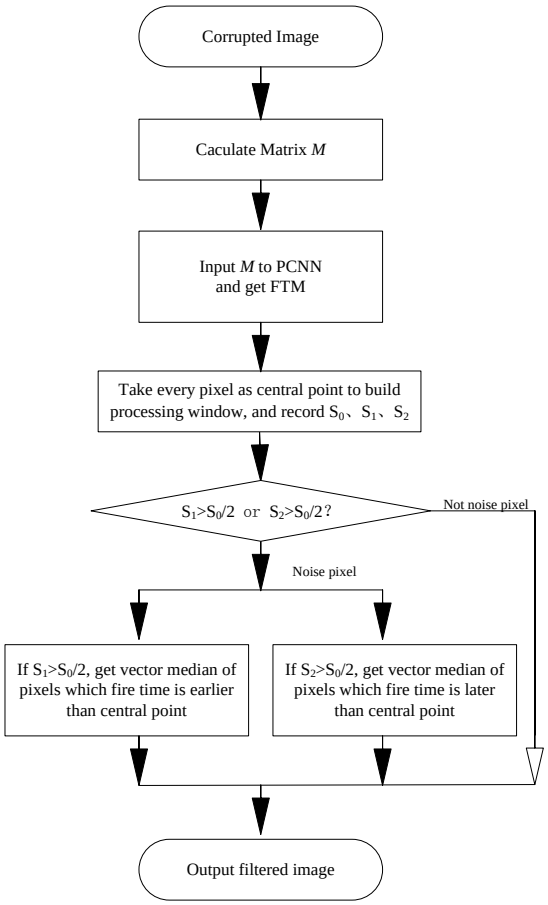


Fig 2. PCNN-VMF filter working flow.

IV. EXPERIMENTAL RESULTS

The primary goal of all filtering algorithms presented in this paper is to remove impulses and outliers from the image. This type of noise is often introduced through bit errors [5], especially during the scanning or transmission over the noisy information channel.

The achieved results were evaluated by the commonly used objective criteria [39, 41], such as the mean absolute error (MAE), the mean square error (MSE), and the normalized color difference (NCD).

The methods were tested using test image Lena, Airplane, Baboon, Fruits. Size of each test image is 256×256. We added impulse noise with p_v=0.05 to test image Lena, p_v=0.10 to test image Airplane, p_v=0.20 to test image Baboon, p_v=0.30 to test image Fruits. Then we use our PCNN-VMF, VMF, BVDF, DDF (g=0.25), Rank SVMF and Mean SVMF on the image. Table I-IV and Fig. 3-6 show the experimental results.

The results show that PCNN is superior to the comparison algorithms in removal noise and image detail preservation. Especially when p_v>0.2, vector filters brings distort of image, but PCNN not only preservation the details but also remove the noise.

TABLE I.
Comparison of the presented algorithms using impulsive noise corruption p_v=0.05

Method/criterion	MSE	MAE	NCD $\times 10^{-4}$
PCNN-VMF	95.37	3.23	59.26
VMF	162.21	6.74	116.26
BVDF	171.26	6.93	122.20
DDF	153.18	5.96	109.55
Rank SVMF	95.30	3.12	62.72
Mean SVMF	116.71	4.81	83.54

TABLE II.
Comparison of the presented algorithms using impulsive noise corruption p_v=0.1

Method/criterion	MAE	MSE	NCD $\times 10^{-4}$
PCNN-VMF	115.23	4.01	69.02
VMF	175.50	7.11	118.62
BVDF	181.92	7.09	125.26
DDF	163.02	6.75	105.00
Rank SVMF	120.91	4.03	75.21
Mean SVMF	136.99	4.99	95.52

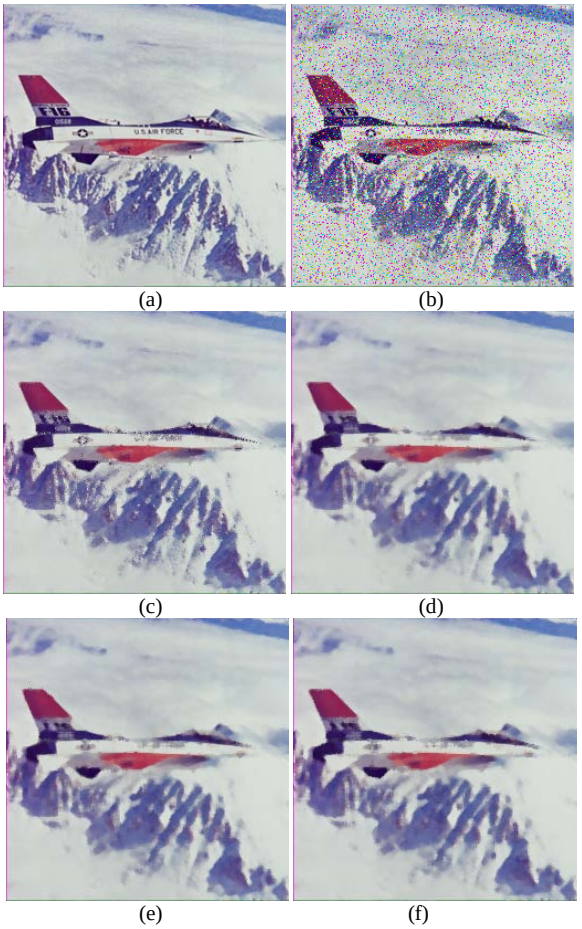
TABLE III.
Comparison of the presented algorithms using impulsive noise corruption p_v=0.2

Method/criterion	MAE	MSE	NCD $\times 10^{-4}$
PCNN-VMF	151.89	4.92	90.24
VMF	207.34	7.95	127.39
BVDF	221.35	8.23	138.96
DDF	195.41	7.31	117.25
Rank SVMF	158.22	5.52	96.77
Mean SVMF	169.50	5.79	99.28

TABLE IV.
Comparison of the presented algorithms using impulsive noise corruption p_v=0.3

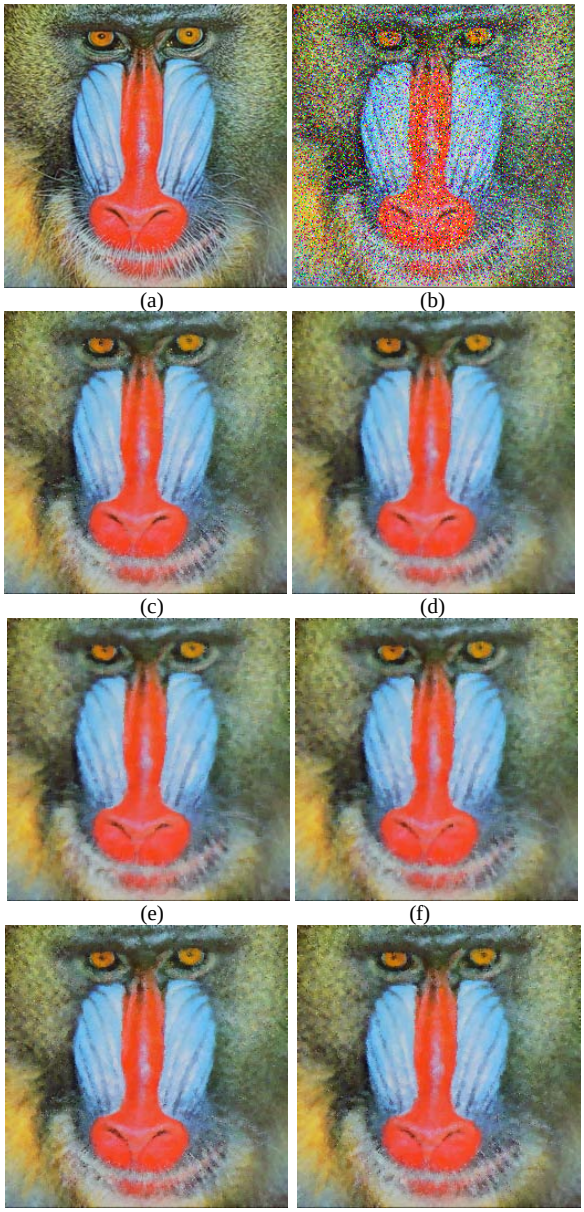
Method/criterion	MAE	MSE	NCD
PCNN-VMF	196.57	6.77	105.12
VMF	237.66	8.59	145.14
BVDF	274.10	8.92	161.48
DDF	236.55	7.79	161.72
Rank SVMF	209.31	7.11	115.71
Mean SVMF	219.71	7.61	136.78

Fig 3. Original Lena image, impulsive noise (p_v=0.05) image and filtered outputs.
(a) Original Lena image; (b) Noise image; (c) PCNN-VMF; (d) VMF; (e) BVDF; (f) DDF; (g) Rank SVMF; (h) Mean SVMF.



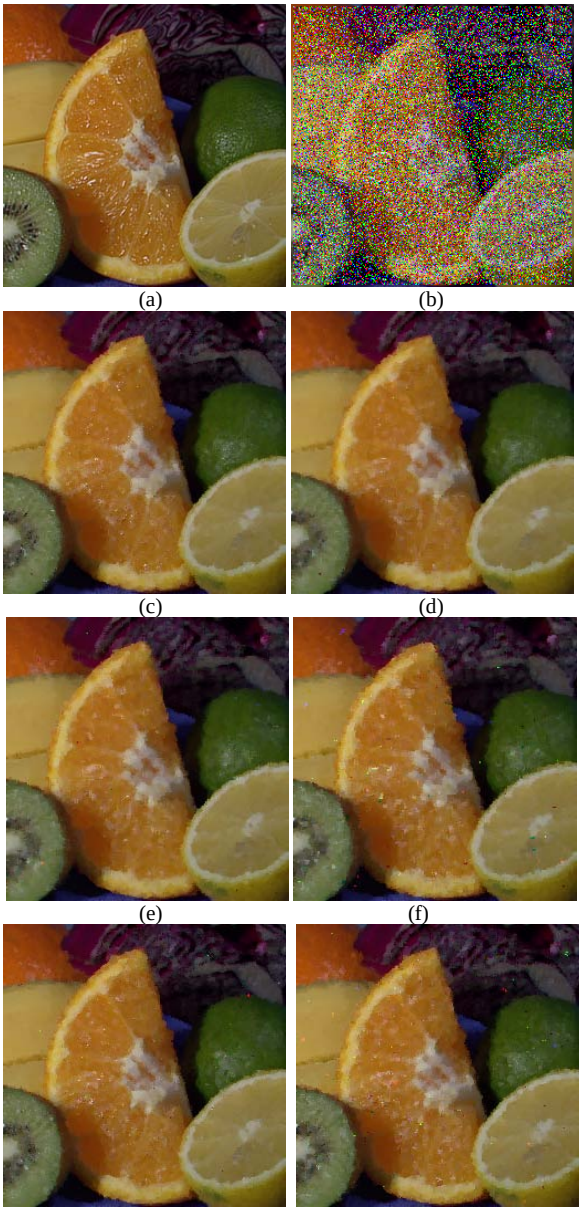
(g) (h)

Fig 4. Original Airplane image, impulsive noise (p_v=0.10) image and filtered outputs.
(a) Original Airplane image; (b) Noise image; (c) PCNN-VMF; (d) VMF; (e) BVDF; (f) DDF; (g) Rank SVMF; (h) Mean SVMF.



(a) (b) (c) (d) (e) (f) (g) (h)

Fig 5. Original Baboon image, impulsive noise (p_v=0.20) image and filtered outputs.
(a) Original Baboon image; (b) Noise image; (c) PCNN-VMF; (d) VMF; (e) BVDF; (f) DDF; (g) Rank SVMF; (h) Mean SVMF.



(a) (b) (c) (d) (e) (f) (g) (h)

Fig 6. Original Fruits image, impulsive noise (p_v=0.30) image and filtered outputs.
(a) Original Fruits image; (b) Noise image; (c) PCNN-VMF; (d) VMF; (e) BVDF; (f) DDF; (g) Rank SVMF; (h) Mean SVMF.

V. CONCLUSION

In this paper, a new color image filtering framework which based on PCNN has been proposed.

The achieved results show excellent detection and image detail preservation capabilities of the new approach, while still holding the impulsive noise attenuation characteristics of standard vector filters. The new filters clearly outperform the standard vector filtering schemes as well as their adaptive modifications. In our experiments, the best results were achieved by PCNN-VMF scheme.

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