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A Modified Noncausal Prediction Based Switching Median Filter For The Removal Of Impulse Noise

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Abstract

In this paper, we propose a switching based median filter for the preservation of better image details while reducing the streaking effect in gray scale images corrupted by impulse noise at higher noise density. The filter is based on the technique of substitution of corrupted pixels prior to estimation. It effectively compressing the noise in two stages. First, it detects the noisy pixel by using the tri-state median (TSM) filter. In the next stage, the noisy pixels are first substituted by the 2D noncausal linear prediction technique and subsequently replaced by the median value. Extensive simulations are carried out to validate our proposed scheme. Experimental results show improvements both visually and quantitatively compared to that of the state-of-the art switching based median filters for the removal of impulse noise at different densities.

1. Introduction

All Digital images are frequently corrupted by impulse noise during the image acquisition and/or transmission process. Preserving the image details and attenuation of noise are the two common and essential aspects of image processing which are always contradictory in nature. So the research emphasis is on the removal of impulse noise while keeping the loss of image details minimum as low as possible. There are two types of impulse noises, namely, the fixed valued impulse noise known as salt and pepper noise and the random valued impulse noise. Linear filtering techniques are not satisfactory for the removal of impulse noise while nonlinear techniques have been found superior and provides more satisfactory performance in preserving better image details. The most common nonlinear filter is the standard median (SM) filter [1]. The SM filter replaces the each pixel of the image by the median value obtained from the corresponding neighbourhood window centered at this pixel. It performs effectively at low noise density ratio but at the cost of blurring the image. One solution to overcome this problem is the weighted median (WM) filter [2] which gives more weight to some values within the window than others. The special case of the WM filter is the center weighted median (CWM) [3] filter and it gives more weight only to the center value of the window. However they do not perform well for the higher noise densities. The drawback of these filters is that they do not detect a priori whether a pixel in image is actually corrupted or not by impulse and simply replaces every pixel by the median value of the pixels in its fixed neighborhood. A better way to circumvent this drawback is to incorporate some decision-making processes or switching action in the filtering framework. The switching based median filter performs well for the removal of impulse noise in comparison to the CWM filter with preservation of better image details. Some of the state-of-the-art switching median filters are the rank-conditioned mean (RCM) [4], the signal-dependent rank ordered mean (SDROM)[5], the tri-state median (TSM) [6] filter, the adaptive center weighted median (ACWM) [7] filter, the directional weighted median (DWM) [8], the adaptive switching median (ASWM) [9], and the new switching based median (NSWM) [10] filters. In the tri-state median (TSM) filter, multiple thresholds are considered in detection of the pixels corrupted by noise and then the detected pixels are replaced by the value obtained from the tri-state decision in the current window. Another recently proposed switching based median filter with preservation of better image details on images corrupted by the salt and pepper noise at high noise ratios is the new switching based median (NSWM) filter. The NSWM filter uses the concept of substitution of corrupted pixels prior to estimation but it employs the causal 1D linear prediction technique for the substitution of all corrupted pixels within a window. This filter has been found to perform quite impressive for the removal of salt and pepper noise. However, NSWM filter does not taking the 2D structure of an image for the prediction of the pixels which are noisy and therefore does not exploit the interline dependence of the pixels. So the performance of the NSWM filter explicitly may be further improved by considering the natural structure of the pixels in an image. It applies a very simple technique for the detection of the noisy pixels. In NSWM filter, any pixel having a value of either 0 or 255 are considered as the corrupted pixels. However, in practice this may not be happen in real scenario. Because in practice the uncorrupted image may also have some pixels of values either 0 or 255, hence there is a probability of false detection of some noise free pixels. In this paper, we are presenting a two stage switching based linear median filter to remove the impulse noise from gray scale images. Firstly, the pixels which are corrupted by noise are detected by the detection concept of the tri-state median (TSM) filter. Secondly, the detected noisy pixel is substituted by using the 2D noncausal linear prediction technique and subsequently the pixel is estimated from the predicted pixel and its neighbors. The noise free pixels in the image are left unchanged as earlier. The experiments are carried out in details to validate the proposed method both qualitatively and quantitatively. The rest of the paper is organized as follows. In Section II, we present the impulse noise model for gray scale images. Section III gives the overview of the detection technique of TSM filter. Section IV gives overview of non causal linear prediction in gray scale images. The proposed non causal switching based median filter is discussed in Section V. Section VI gives the experimental results using different test images. Finally, conclusions are drawn in Section VII.

2. Impulse noise model

Consider an 8-bit gray scale image $\mathbf{X}$. Let $Y(i,j)$ be the gray value of the noisy image $\mathbf{Y}$ at pixel (i,j) and $W(i,j)$ be a window centered at (i,j). We assume here the following impulse noise model

$$Y(i,j)=\begin{cases} X(i,j)\text{ , with probability } 1-\gamma \\ R(i,j)\text{ , with probability } \gamma \end{cases} \quad (1)$$

Where $X(i,j)$ and $R(i,j)$ denote the pixel values at location (i,j) in the original image and the noisy image, respectively and γ is the noise ratio/density. In an 8-bit gray scale image, the salt and pepper noise $R(i,j)$ can take either 0 or 255 where as random valued impulse noise, $R(i,j)$ is uniformly distributed in [0,255].

3. Tri-state detection

The proposed scheme adopts conceptual technique from the impulse detection stage of the TSM filter, a brief review of this filter has been given below.

Consider a 3×3 window $\mathbf{W}$ centered at $Y(i,j)$. Define an observation vector containing the pixels in the neighbourhood of $Y(i,j)$ and obtained by a left-right, top-to-bottom scan of the window and another window giving weight to the central value :

$$\begin{aligned} d_1 &= |Y(i,j)-Y_{SM}(i,j)| \\ d_2 &= |Y(i,j)-Y_{CWM}(i,j)| \end{aligned} \quad (2)$$

Here, d_1 and d_2 are the absolute difference. $Y_{SM}(i,j)$ is the median value obtained from SM filter and $Y_{CWM}(i,j)$ is the median value of CWM filter. Consider $Y(i,j)$ to be noisy if it satisfies the condition $d_2 > T_1$ and $d_2 \le T_2 < d_1$ otherwise noise free. Where, T_1 and T_2 are threshold values.

4. Noncausal linear prediction

In the noncausal linear prediction technique, a noncausal neighbourhood of pixel is considered to make prediction of the current pixel. The 2D linear prediction value of the central pixel $Y(i,j)$ is given by [11]:

$$\hat{Y}(i,j)=\mathbf{Y}^T\text{a}, \quad (3)$$

Where,

$$\mathbf{Y}=[\{Y(i,j-1)+Y(i,j+1)\},Y(i-1,j)+Y(i+1,j)]^T$$

considering samples at horizontal row and vertical column only in the prediction window. Here, $\text{a}=[a_{0,1},a_{1,0}]^T$ signifies the coefficient of prediction vector. The coefficient of prediction are related with the autocorrelation functions by the following Wiener-Hopf equation [12]:

$$\mathbf{R}_{YY}\mathbf{a} = \mathbf{r}_{Y}.$$

(4) The solution of the above matrix equation gives the prediction coefficient vector Using the symmetry property $\mathbf{R}_{YY}(i, j) = \mathbf{R}_{YY}(-i, -j)$ of the autocorrelation function of wide-sense stationary image random field, it can be shown that [13]:

$$a(-i,-j) = a(i, j). \tag{5}$$

5. The proposed switching filter

This filter is based on the substitution concept of noisy pixels prior to estimation. The proposed scheme consists of two stages. First stage, the noisy pixels are detected by the impulse detection concept of the TSM filter. We adopt the concept of TSM filter because of its accuracy of detection of an impulse with consideration of proper threshold even in the presence of multiple impulses within the sliding window. It considers two increasing thresholds and compared with the value obtained by the absolute difference. The comparison is individually done to detect an impulse on the basis of the detection concept of noisy pixel as explained in the section III.

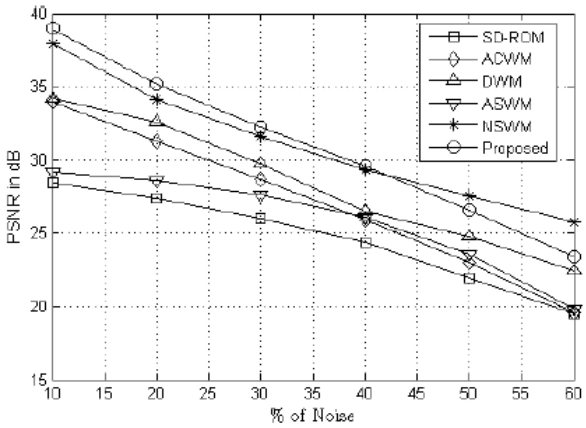
Second stage, if any pixel is detected as noisy it is substituted by noncausal linear prediction from the neighbourhood pixels in the current window prior to estimation as described in Section IV. Then the corrupted pixel is replaced by the median value obtained from its neighbourhood pixels within that window. This strategy of prediction and substitution is found to be very effective than the ordinary conventional method of replacement of an impulse by the median value obtained in the switching based median filters because the noisy central pixel is not included directly in the filtering window to estimate the median value [10]. Instead, it is first smoothed by predicting its value from its noncausal neighbourhood in the image prior to estimation. In this present development scheme of the algorithm, we consider the 2D noncausal linear prediction technique in order to have the minimum computational complexity of the propose algorithm. The noise free pixels in the image are kept unchanged.

The proposed algorithm mainly executes the following steps recursively until every pixel in the image are processed:

- *Input* $\mathbf{Y}$
- Repeat
- Select a 3×3 window $\mathbf{W}$ with $Y(i, j)$ being its center.
- Apply the impulse detection stage of the TSM filter described in Section III for the pixels in $\mathbf{W}$ with slight modification of tri-state switching comparison of threshold. The threshold comparison of TSM is modified as shown in below.
  If any pixel of the corresponding window satisfies either one of the condition given $T_1 < d_2$ or $d_2 < T_2 < d_1$ or $d_2 \le T_2 < d_1$
  Then the pixel considered as noisy. The absolute computation of d_1 and d_2 are as explained in the section III.
- If $Y(i, j)$ is noisy, carry out the first-order noncausal linear prediction explained in Section IV and substitute the same with $\hat{Y}(i, j)$ using Equation (3) otherwise it is kept unaltered.
- Arrange the pixels in $\mathbf{W}$ with center $\hat{Y}(i, j)$ or or to an 1D array Z.
- Find the median value of Z.
- Finally, replace $Y(i, j)$ by the median value.
- Until all $Y(i, j)$ is in Y.

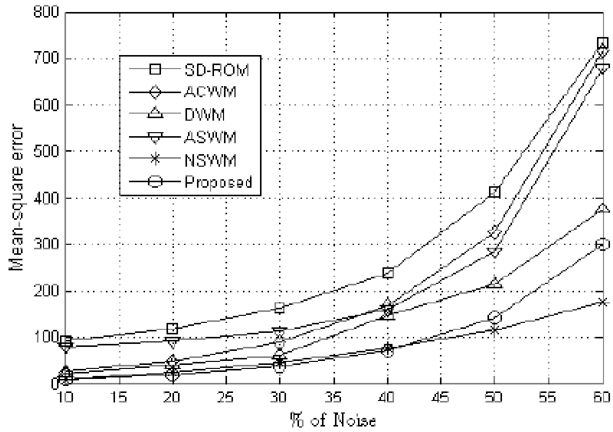
Fig.1. Performance of different filters for “Lena” image with 40% salt and pepper noise. (a) Noisy. (b) SD-ROM. (c) ACWM. (d) ASWM. (e) DWM. (f) NSWM. (g) Proposed and (h)

Fig.2. Performance of different filters for “Barbara” image with 50% salt and pepper noise. (a) Noisy. (b) SD-ROM. (c) ACWM. (d) ASWM. (e) DWM. (f) NSWM. (g) Proposed and (h) Original.



(a)

Fig.3. Performance comparison of different methods for filtering “Cameraman” image degraded by various levels of salt and pepper noise. (b) PSNR vs. % of



(b)

Fig.4. Performance comparison of different methods for filtering “Cameraman” image degraded by various levels of salt and pepper noise. (b) MSE vs. % of

TABLE I.
PERFORMANCES OF VARIOUS FILTERS ON "LENA" IMAGE AT DIFFERENT NOISE DENSITIES. (A) PSNR IN DB AND (B) MSE

A

Method	% 0f Noise					
	10	20	30	40	50	60
SD-ROM[5]	32.98	31.45	29.32	27.02	23.93	20.16
TSM[6]	31.11	30.25	24.76	19.97	16.54	13.44
ACWM[7]	39.93	35.57	31.68	28.13	23.99	20.32
ASWM[9]	33.27	32.78	31.06	29.21	25.51	20.69
NSWM[10]	41.52	37.23	34.30	31.24	30.52	28.44
Proposed	**42.17**	**37.96**	**34.73**	**31.53**	**28.76**	**24.94**

B

Method	% 0f Noise					
	10	20	30	40	50	60
SD-ROM[5]	32.69	46.50	76.04	131.13	272.96	625.75
TSM[6]	39.33	61.30	217.1	665.5	1513.1	3107.3
ACWM[7]	6.59	18.02	44.13	99.91	259.25	603.69
ASWM[9]	30.04	35.73	50.86	77.91	182.62	554.12
NSWM[10]	4.21	11.17	20.81	38.78	57.64	92.99
Proposed	**3.39**	**8.53**	**18.82**	**37.98**	**90.96**	**224.90**

TABLE II.
PERFORMANCES OF VARIOUS FILTERS ON "CAMERA MAN" IMAGE AT DIFFERENT NOISE DENSITIES. (A) PSNR IN DB AND (B) MSE

A

Method	% 0f Noise					
	10	20	30	40	50	60
SD-ROM[5]	28.43	27.39	26.01	21.70	20.15	17.37
TSM[6]	28.23	24.90	21.85	18.77	15.35	12.23
ACWM[7]	28.29	25.57	23.72	21.92	20.29	17.58
ASWM[9]	29.02	25.34	23.88	22.61	20.88	17.88
NSWM[10]	32.15	30.64	28.05	26.04	24.68	22.92
Proposed	**32.96**	**32.06**	**30.26**	**27.48**	**25.60**	**23.57**

B

Method	% 0f Noise					
	10	20	30	40	50	60
SD-ROM[5]	93.14	118.50	163.26	237.94	412.85	732.64
TSM[6]	98.43	210.0	423.4	930.2	1892.6	3889.0
ACWM[7]	25.90	48.63	88.52	167.23	326.14	715.70
ASWM[9]	79.43	91.24	112.79	160.04	283.30	679.61
NSWM[10]	10.18	25.77	45.19	75.72	115.33	174.03
Proposed	**8.26**	**19.82**	**38.65**	**71.62**	**142.37**	**298.99**

6. Experimental results

Simulations are carried out to evaluate the performance of the proposed scheme to remove the impulse noise in different standard gray scale test images. The test images are "Lena" 512×512, "Barbara" 512×512, "Boat" 512×512, and "Cameraman" 256×256 . All these images are artificially corrupted with the salt impulse noise at different noise density varying from 10% to 60%. Noisy pixels are detected by the detection technique of TSM filter . It is implemented by considering a 3×3 window. The two increasing thresholds selected for the TSM filter are from the following set of values: $T1$ =20 *and* $T2$ = *40*. The first-order 2D non causal linear prediction is carried out considering a 3×3 neighbourhood window around the center pixel. Considering its position as $(0,0)$ in the window, the estimation of coefficients of prediction are computed by Equation (4). The central position pixel is predicted by Equation (3). We have compared the performance of the proposed scheme with other switching based median filters includes the SD-ROM, the ACWM, the DWM, the ASWM, and the NSWM filters in terms of the mean-square error (MSE) and the peak signal-to-noise ratio (PSNR).

Table I shows the comparison of output PSNR and MSE values for different filters for the "Lena" image at different percentages of salt and pepper noise. Similarly, Table II shows the corresponding results for the "Cameraman" image. The results clearly shows that the proposed filtering method outperforms the state of- the-art in terms of PSNR and MSE values for both the test images when corrupted by the impulse noise up to 40%. It is observed that the performance of the proposed method deteriorates for noise densities above this value as compared to that of the NSWM filter. This is because at higher noise densities the probability of getting more than one impulse within the 2D neighbourhood window becomes higher, leading to poor prediction of the central pixel, whereas in the NSWM filter the prediction of the center pixel is done from the noise free pixels in a sorted 1D array. However, the results show that the proposed filter outperforms the SD-ROM filter, the TSM filter, and the ASWM filter even at noise ratios beyond 60%.

Fig. 1(b)-(g) show the outputs of various filter for the "Lena" image when 40% of the total pixels of the image are corrupted by the impulse noise. From a visual inspection of the output images, it is observed that the proposed filter not only able to remove the noise but also successfully preserves the better image detail features in the image. Similarly, Fig. 2(b)-(g) show the results for the "Barbara" image when corrupted by 50% of impulse noise. As expected, it is observed that the visual quality of the output of the proposed filter degrades as the noise ratio is increased to 50% or more. The performances of the proposed method and other considered filters for "Cameraman" image corrupted by impulse noise at different levels in terms of PSNR and MSE are reported in Fig.3 and Fig.4. The results of our proposed scheme show that the method is clearly perform better than those other methods up to 40-45% of noise in terms of both PSNR and MSE.

7. Conclusions

An improved switching based median filter has been proposed based on the concept of substitution, prior to estimation for the removal of impulse noise from gray scale images. The algorithm is work in two stages. In the first stage, the impulses are detected by the impulse detection method of the tri-state detection technique. In the second stage, the noisy pixel is first predicted using the 2D non causal linear prediction method and subsequently it is replaced by the median of its neighbourhood pixels. The experimental results show that the proposed filter outperforms than other schemes like the SD-ROM, the ACWM, the TSM, the ASWM, and the NSWM filters both qualitatively and quantitatively up to medium level of impulse noise corruption. However, at high noise levels NSWM filter performs quite well then the proposed filter. The NSWM filter is based on first order causal linear prediction only, and does not consider the 2D correlation of the image pixels. Therefore, it results in blurring of the detail features in the image at low to medium noise levels as opposed to the proposed filtering scheme. This work is currently in progress to extend the proposed scheme for the removal of random valued impulse noise.

8. References

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