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Research Article

A Nonlinear Decision-Based Algorithm for Removal of Strip Lines, Drop Lines, Blotches, Band Missing and Impulses in Images and Videos

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A decision-based nonlinear algorithm for removal of strip lines, drop lines, blotches, band missing, and impulses in images is presented. The algorithm performs two simultaneous operations, namely, detection of corrupted pixels and estimation of new pixels for replacing the corrupted pixels. Removal of these artifacts is achieved without damaging edges and details. The algorithm uses an adaptive length window whose maximum size is 5×5 to avoid blurring due to large window sizes. However, the restricted window size renders median operation less effective whenever noise is excessive in which case the proposed algorithm automatically switches to mean filtering. The performance of the algorithm is analyzed in terms of mean square error [MSE], peak-signal-to-noise ratio [PSNR], and image enhancement factor [IEF] and compared with standard algorithms already in use. Improved performance of the proposed algorithm is demonstrated. The advantage of the proposed algorithm is that a single algorithm can replace several independent algorithms required for removal of different artifacts.

1. INTRODUCTION

It is well known that linear filters are not quite effective in the presence of non-Gaussian noise. In the last decade, it has been shown that nonlinear digital filters can overcome some of the limitations of linear digital filters [1]. Median filters are a class of nonlinear filters and have produced good results where linear filters generally fail [2]. Median filters are known to remove impulse noise and preserve edges. There are a wide variety of median filters in the literature. In remote sensing, artifacts such as strip lines, drop lines, blotches, band missing occur along with impulse noise. Standard median filters reported in the literature do not address these artifacts. Strip lines are caused by unequal responses of elements of a detector array to the same amount of incoming electromagnetic energy [3]. This phenomenon causes heterogeneity in overall brightness of adjacent lines. Drop line [3] occurs when a detector does not work properly for a short period. Impulse noise appears when disturbing microwave energies are present or the sensor/detector is degraded. Band missing [3] is a serious problem and is caused by corruption of two or more drop/strip lines continuously. For removal of these artifacts, generally separate methods are employed. Strip lines and drop lines are considered as line scratches by Silva and Corte-Real [4] for image sequences. According to him, a positive type film suffers from bright scratches and negative film suffers from dark scratches. Milady has considered only the dark scratches; if bright scratches exist he inverted them and used the same algorithm. Silva and Corte-Real [4] gives a remedy for removing the blotches and line scratches in images. He has considered only vertical lines (which are narrow) and the blotches as impulsive with constant intensity having irregular shapes. Kokaram [5] has given a method for removal of scratches and restoration of missing data in the image sequences based on temporal filtering. Additionally, impulse noise is a standard type of degradation in remotely sensed images. This paper considers application of median-based algorithms for removal of impulses, strip lines, drop lines, band missing, and blotches while preserving edges. It has been shown recently that an adaptive length algorithm provides a better solution for removal of impulse noise with better edge and fine detail preservation. Several adaptive algorithms [6–9] are available for removal of impulse noises. However, none of these algorithms addressed the problem of strip lines, drop lines, blotches, and band missing in images. The objective of this paper is to propose an adaptive length median/mean algorithm that can simultaneously remove impulses, strip lines, drop lines, band missing, and blotches while preserving edges. The advantage of the proposed algorithm is that a single algorithm with improved performance can replace several independent algorithms required for removal of different artifacts.

2. DEGRADED IMAGE MODEL

Blotches are impulsive-type degradations randomly distributed with irregular shapes of approximately constant intensity. These artifacts last for one frame. In the degraded regions there is no correlation between successive frames. Blotches are originated by dust, warping of the substrate or emulsion, mould, dirt, or other unknown causes. Blotches in film sequences can be either bright or dark spots. If the blotch is formed on the positive print of the film, then the result will be a bright spot, however if it is formed on the negative print, then in the positive copy, we will see a dark spot.

Line scratches are narrow vertical, or almost vertical, bright/dark lines that affect a column or a set of columns of the frame. They are also impulsive type artifacts. Line scratches, unlike blotches, can persist for several frames in the same position. The erosion that exists when the film material is run against a foreign object in the projection device causes the line scratches. The transfer process between film material and telecine can also produce scratches.

It is difficult to propose a general mathematical model for the effect of the abrasion of the film causing the scratches due to the high number of variables that are involved in the process. However, it is possible to make some physical and geometrical considerations regarding the brightness, thickness, and vertical extent of the line. Line scratches can be characterized as follows: (i) they present a considerable higher or lower luminance than their neighborhoods; (ii) they tend to extend over most of the vertical length of the image frame and are not curved; and (iii) they are quite narrow, with widths no larger than 10 pixels for video images. These features can be used to define a model. The degraded image model considered is

$$a(x, y) = I(x, y)\big(1 - b(x, y)\big) + b(x, y)c(x, y), \tag{1}$$

where $I(x, y)$ is the pixel intensity of the uncorrupted signal, $b(x, y)$ is a detection variable which is set to 1 whenever pixels are corrupted and 0 otherwise, $c(x, y)$ is the observed intensity in the corrupted region. This model is applied in this work to images degraded by impulses, strip lines, drop lines, band missing, and blotches.

If $b(x, y) = 0$,

$$\text{then } a(x, y) = I(x, y)(1 - 0) + 0 \cdot c(x, y) = I(x, y), \tag{2}$$

where $I(x, y)$ is the original pixel value (uncorrupted pixel).

If $b(x, y) = 1$,

$$\text{then } a(x, y) = I(x, y)(1 - 1) + 1 \cdot c(x, y) = c(x, y), \tag{3}$$

where $c(x, y)$ is the observed intensity in the corrupted region.

Assume that each pixel at (x, y) is corrupted by an impulse with probability p independent of whether other pixels are corrupted or not. For images corrupted by a negative or positive impulse, the impulse corrupted pixel $e(x, y)$ takes on the minimum pixel value $s_{\min}$ with probability p, or $s(x, y)$ the maximum pixel value $s_{\max}$ with probability $1 - p$. The image corrupted by blotches or scratches (impulsive) can be now modeled as

$$\begin{aligned} c(x, y) = e(x, y) &\quad \text{with } p \\ s(x, y) &\quad \text{with } 1 - p. \end{aligned} \tag{4}$$

This, in fact, is the model that describes impulse noise in the literature. However, the existing impulse filtering algorithms do not effectively remove blotches and scratches. In Section 3, an adaptive length median/mean filter algorithm is developed that removes blotches, scratches effectively along with impulse noise.

3. AN ADAPTIVE LENGTH MEDIAN/MEAN FILTER

Median filter is a nonlinear filter, which preserves edges while effectively removing impulse noise. Median operations are performed by row sorting, column sorting, and diagonal sorting in images [10]. General median filters often exhibit blurring for large window sizes, or insufficient noise suppression for small window sizes. Adaptive length median filter overcomes these limitations of general median filters. Lin and Willson [6] proposed an adaptive window length median filter algorithm which can achieve a high degree of noise suppression and still preserve image sharpness; however, the algorithm performs poorly for mixed impulse noise consisting of positive and negative impulses. Lin's algorithm is modified by Hwang and Haddad [7]. Huang's algorithm takes into account both positive and negative impulses for simultaneous removal; but it acts poorly on the strip lines, drop lines, and blotches.

Unlike these adaptive algorithms based on edge detection [6, 7], the proposed algorithm is based on artifacts detection. The positive and negative impulses are removed separately. In contrast to general adaptive length median filters, the window size is restricted to a maximum of 5×5 to minimize blurring. Restriction of window size renders the median operation less effective whenever noise is excessive (the output of the median filter may turn out to be a noisy pixel). In this situation, the algorithm switches to compute the average of uncorrupted pixels in the window (the probability of getting the noisy pixel as filtered output is lower because the averaging takes only uncorrupted pixels into account). The proposed algorithm removes the strip lines, drop lines, blotches along with impulses even at higher noise densities.

4. ILLUSTRATIONS

The algorithm consists of two operations: first is the detection of degraded pixels, and the second operation is the replacement of faulty pixels with the estimated values.

Let the pixel be represented as $P(i, j)$ and the number of corrupted pixels in the window $W(i, j)$ be "n." Let $P_{\max} = 225$ and $P_{\min} = 0$ be the corrupted pixel values and $P(i, j) \neq 0, 255$ represent uncorrupted pixels.

Case 1. Consider window size 3×3 with typical values of pixels shown as an array below. If $P(i, j) \neq 0, 255$, then the pixels are unaltered. For the array shown, there are no corrupted pixels in the array; therefore, the pixels are unaltered.

123	214	156
236	167	214
123	234	56

(5)

If $P(i, j) = 0$ or 255, then the following cases are considered (a flow chart illustration of the complete algorithm is shown in Figure 1) .

Case 2. If the number of corrupted pixels "n" in the window $W(i, j)$ is less than or equal to 4, that is, $n \leq 4$, then two-dimensional window of size 3×3 is selected and median operation is performed by column sorting, row sorting, and diagonal sorting. The corrupted $P(i, j)$ is replaced by the median value.

Corrupted matrix

255	214	123
0	**255**	214
123	234	0

Row sorting $\longrightarrow$

123	214	255
0	214	255
0	123	234

Column sorting $\downarrow$

0	123	234
0	214	255
123	214	255

Diagonal sorting $\longrightarrow$ $\downarrow$

0	123	123
0	**214**	255
234	214	255

(6)

Case 3. If the number of corrupted pixels "n" in the window $W(i, j)$ is between 5 and 12, that is, $5 \leq n \leq 12$, then perform 5×5 median filtering and replace the corrupted values by the median value.

Corrupted matrix

123	0	156	255	234
255	0	214	98	0
0	234	255	133	190
199	255	234	255	0
255	167	210	198	178

Row sorting $\longrightarrow$

0	123	156	234	255
0	0	98	214	255
0	133	190	234	255
0	199	234	255	255
167	178	198	210	255

(7)

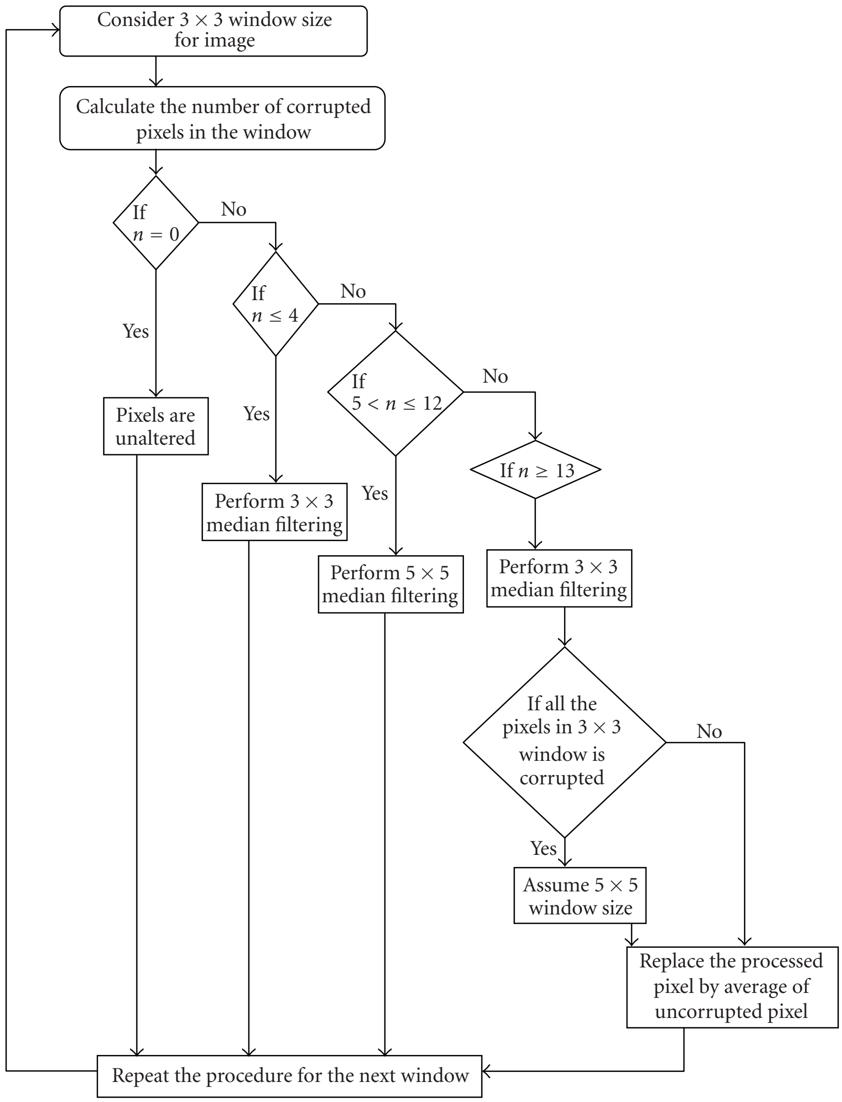
Column sorting $\downarrow$

0	0	98	210	255
0	123	156	214	255
0	133	190	234	255
0	178	198	234	255
167	199	234	255	255

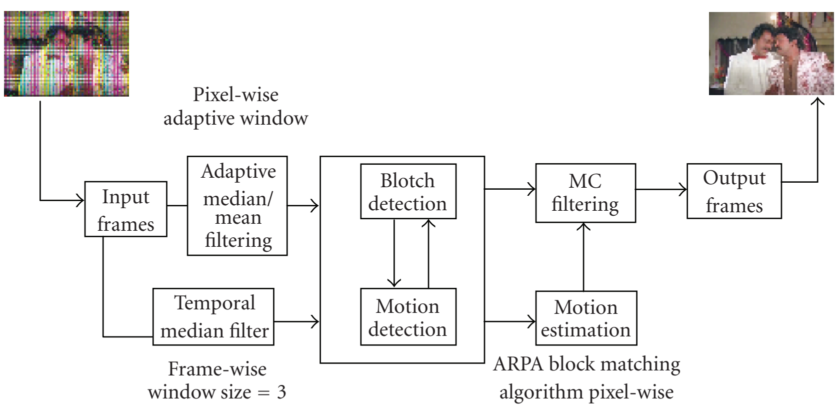
Diagonal sorting

0	0	98	210	167
0	123	156	178	255
0	133	190	234	255
0	214	198	234	255
255	199	234	255	255

Case 4. (i) If the number of corrupted pixels "n" in the window $W(i, j)$ is greater than 13, that is, $n \geq 13$ (a typical case is shown as an array below) increasing the window size may lead to blurring; choose 3×3 median filtering. On



(a) Flow chart of the proposed algorithm.



(b) Block diagram of the proposed algorithm for video sequences.

Figure 1

median filtering with smaller window sizes, the output may happen to be noise pixels whenever the noise is excessive. In this case, find the average of uncorrupted pixels in the window and replace the corrupted value by the average value. The average of the pixel value in the window is taken instead of median value, if the number of uncorrupted pixels in the window is even (it is convenient to define median for odd number of pixels).

$$
\begin{array}{|c|c|c|c|c|}\hline 123 & 0 & 156 & 255 & 234 \\ \hline 255 & 255 & 123 & 255 & 0 \\ \hline 0 & 255 & \mathbf{255} & 133 & 145 \\ \hline 199 & 0 & 255 & 0 & 255 \\ \hline 255 & 167 & 0 & 198 & 178 \\ \hline \end{array}
\quad
\begin{array}{|c|c|c|}\hline 255 & 123 & 255 \\ \hline 255 & \mathbf{255} & 133 \\ \hline 0 & 255 & 0 \\ \hline \end{array}
\quad
\begin{array}{|c|c|c|}\hline 255 & 123 & 255 \\ \hline 255 & \mathbf{128} & 133 \\ \hline 0 & 255 & 0 \\ \hline \end{array}
\qquad (8)
$$

(133 and 123 are the uncorrupted pixels) $(133 + 123)/2 = 128$

(ii) If all the pixels in 3×3 windows are corrupted (a typical case is shown as an array below), then perform 5×5 median filtering. On median filtering, the output may happen to be noise pixels as in Case 4. Find the average of uncorrupted pixels in the window and replace the corrupted value by the average value.

$$
\begin{array}{|c|c|c|c|c|}\hline 123 & 0 & 156 & 255 & 234 \\ \hline 255 & 255 & 0 & 255 & 0 \\ \hline 0 & 255 & \mathbf{255} & 255 & 145 \\ \hline 199 & 0 & 255 & 0 & 255 \\ \hline 255 & 167 & 0 & 198 & 178 \\ \hline \end{array}
\quad
\begin{array}{|c|c|c|}\hline 255 & 0 & 255 \\ \hline 255 & \mathbf{255} & 255 \\ \hline 0 & 255 & 0 \\ \hline \end{array}
$$

$$
\begin{array}{|c|c|c|c|c|}\hline 123 & 0 & 156 & 255 & 234 \\ \hline 255 & 255 & 0 & 255 & 0 \\ \hline & 255 & \cancel{255} & 255 & 145 \\ \hline 199 & 0 & 255 & 0 & 255 \\ \hline 255 & 167 & 0 & 198 & 178 \\ \hline \end{array}
\quad
\begin{array}{|c|c|c|c|c|}\hline 123 & 0 & 156 & 255 & 234 \\ \hline 255 & 255 & 0 & 255 & 0 \\ \hline 0 & 255 & \mathbf{175} & 255 & 145 \\ \hline 199 & 0 & 255 & 0 & 255 \\ \hline 255 & 167 & 0 & 198 & 178 \\ \hline \end{array}
\quad
\left\{ \frac{123+156+234+145+199+167+198+178}{8} = 175 \right.
\qquad (9)
$$

175 replaces the corrupted pixel value }

5. IMPLEMENTATION IN VIDEO SEQUENCES

The proposed adaptive median/mean algorithm is applied to video sequences degraded by scratches, blotches, and impulses. Adaptive rood pattern search block matching algorithm [11] is used for motion estimation of the image sequences. Motion estimation and compensation techniques [11] are employed for tracking scratches on frames. Prediction and interpolation are used to estimate motion vectors for video denoising. For fast motion prediction, commonly used technique is block matching (BM) motion estimator. The motion vector is obtained by minimizing a cost function measuring the mismatch between a block and each predictor candidate. The motion estimation (ME) gives motion vector of each pixel or block of pixels which is an essential tool for determining motion trajectories. Due to motion of objects in scene (i.e., corresponding regions in an image sequence), the same region does not occur in the same place in the previous frame as in current one. ARPS [11] algorithm makes use of the fact that the general motion in a frame is usually coherent, that is, if the macro blocks around the current macro block moved in a particular direction, then there is a high probability that the current macro block will also have a similar motion vector. ARPS algorithm uses the motion vector of the macro block to its immediate left to predict its own motion vector. The rood pattern search directly puts the search in an area where there is a high probability of finding a good matching block. The point that has the least weight becomes the origin for subsequent search steps, and the search pattern is changed to small diamond search pattern (SDSP). SDSP is repeated until least weighted point is found to be at the center of the SDSP. The main advantage of this algorithm over diamond search (DS) is that if the predicted motion vector is (0, 0), it does not waste computational time in carrying out large diamond search pattern (LDSP); it rather directly starts using SDSP.

The temporal median filter smoothes out sharp transitions in intensity at each pixel position; it not only denoises the whole frame and removes blotches but also helps in stabilizing the illuminating fluctuations. Temporal median

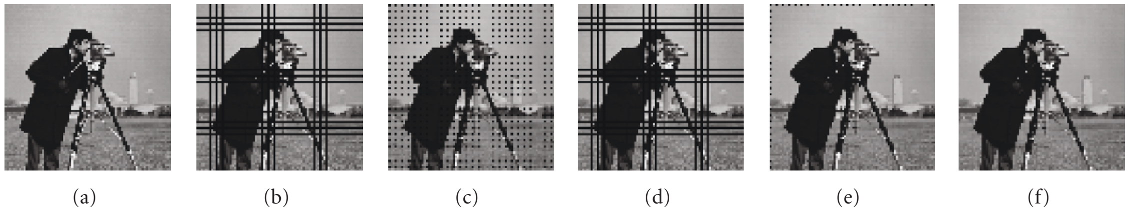


Figure 2: Drop lines removal. (a) Original image. (b) Corrupted by drop lines. (c) Median filtered image. (d) Lin's adaptive length filter. (e) Gonzalez adaptive length filter. (f) Proposed algorithm.

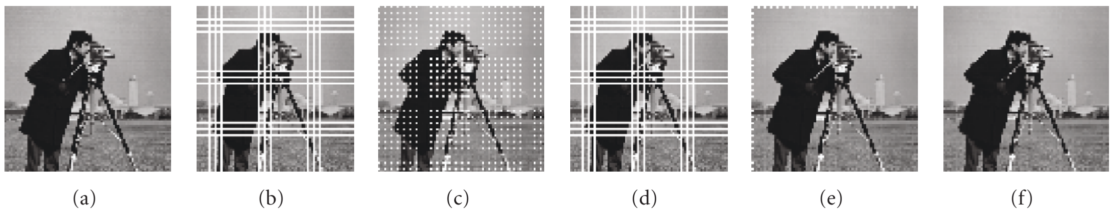


Figure 3: Strip lines removal. (a) Original Image. (b) Corrupted by strip lines. (c) Median filtered image. (d) Lin's adaptive length filter. (e) Gonzalez adaptive length filter. (f) Proposed algorithm.

filtering removes the temporal noise in the form of small dots and streaks found in some videos. In this approach, dirt is viewed as a temporal impulse (single-frame incident) and hence treated by interframe processing by taking into account at least three consecutive frames. Figure 1(b) shows the block diagram of the proposed algorithm implemented in video sequences.

6. RESULTS

The algorithm is tested with different types of degradations, namely, strip lines, drop lines, band missing, blotches, and impulse noise. The results are compared with those of general median filter, Lin's adaptive length median filter, Gonzalez adaptive length median filter and decision-based median filter.

The median filter and Lin's algorithm cause blur in the images and do not remove the degradations (Figures 2(c) and 2(d)–Figures 6(c) and 6(d)). The Gonzalez adaptive algorithm removes the strip lines and drop lines but the edges are not preserved properly (Figures 2(d) and 3(d)) and this algorithm acts very poorly on the blotches and band noises (Figure 4(e)–Figure 6(e)). The proposed algorithm (Figure 2(f)–Figure 6(f)) removes all these degradations more effectively with reduced blurring and edge preservation. The results of the removal of noise at different densities along with degradations are shown in Figures 7 and 8. Lena and Goldhill image are used for comparison. Figure 7 shows 30% of impulse noise with degradations. Figure 8 shows the results of images corrupted with 70% of noise with degradations. Tables 1 and 2 show the MSE, PSNR, and IEF values (at different noise densities and artifacts) computed for median filter, Lin's adaptive length filter, Gonzalez adaptive length filter, decision-based median filter, and the proposed algorithm. The formulas used are

$$\mathrm{MSE} = \frac{1}{mn}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}\left|\left|I(i,j)-K(i,j)\right|\right|^2,$$

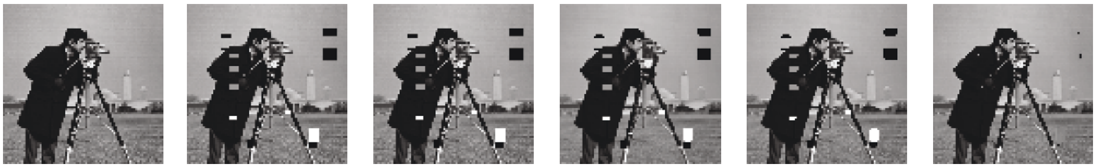
$$\mathrm{PSNR} = 10\cdot\log_{10}\left(\frac{\mathrm{MAX}_I^2}{\mathrm{MSE}}\right) = 20\cdot\log_{10}\left(\frac{\mathrm{MAX}_I}{\sqrt{\mathrm{MSE}}}\right). \tag{10}$$

The performance of several new algorithms [12–14] in respect of impulse noise removal is shown in Table 3. The proposed algorithm also performs well in removal of impulse noise along with some degradation. A table of comparison for removing the impulse noise at 20% noise density for standard median filter (SMF), center weighted median filter (CWMF), decision-based filter (DBMF), Mithra filter, tristate median filter (TSMF), adaptive center weighted median filter (ACWMF), and Luo Filter is shown in Table 3.

The proposed algorithm is tested for 20 frames from the "mannathi mannan" black and white film and "lesa lesa" color film. Figure 9(a) is the white and black line corrupted frame in the film mannathi mannan. Figure 9(b) shows the result of the proposed algorithm. Figures 9(c) and 9(d) show the corrupted and restored frames from the film Lesa Lesa. Similarly, Figures 10(a) and 10(c) show blotches and impulse noise corrupted frame from the mannathi mannan and lesa lesa films. Figures 10(b) and 10(d) show the restored frame. Figure 11(a) shows the PSNR comparison graph for black and white film and Figure 11(b) shows the PSNR comparison graph for color film Lesa Lesa compared with spatial median filtering technique and temporal median technique.

TABLE 1: PSNR, IEF, and MSE for various filters for lena.gif image at different noise densities + degradation. (SMF: standard median filter, AMF: adaptive median filter, DBMF: decision-based median filter, PF: proposed filter).

Noise + degradation	PSNR					IEF					MSE				
	SMF	Lin's	AMF	DBMF	PF	SMF	Lin's	AMF	DBMF	PF	SMF	Lin's	AMF	DBMF	PF
0.05	16.5	16.74	17.25	17.95	30.5	3.47	3.6	4.08	4.7	67.05	1430.2	5212	1219.8	1042.2	751.12
0.3	12.94	12.95	16.68	17.73	27.98	2.55	2.5	6.06	7.6	67.64	3244.4	1030	1400.2	1097.5	754.27
0.5	10.20	10.25	14.78	17.35	25.89	1.81	1.83	5.19	9.42	59.38	6103.8	1561	2239.2	1194.6	756.67
0.7	8.07	8.11	11.09	16.60	22.99	1.37	1.39	2.75	9.89	42.60	10030	2181	4940.4	1419.8	807.8



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

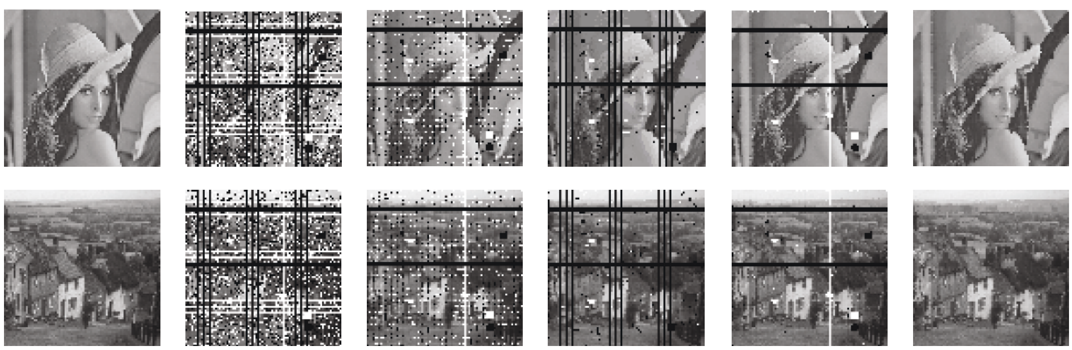
FIGURE 4: Blotches removal. (a) Original Image. (b) Corrupted by blotches. (c) Median filtered image. (d) Lin's adaptive length filter. (e) Gonzalez adaptive length filter. (f) Proposed algorithm.

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

FIGURE 5: White band noise removal. (a) Original Image. (b) Corrupted by white band noise. (c) Median-filtered image. (d) Lin's adaptive length filter. (e) Gonzalez adaptive length filter. (f) Proposed algorithm.

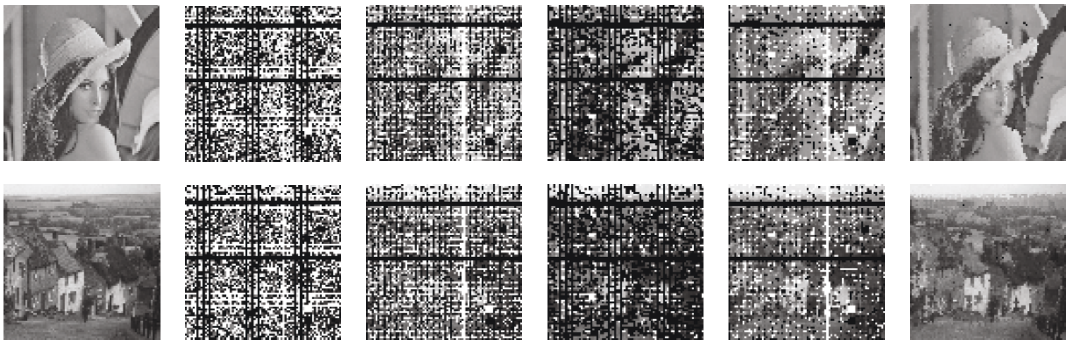
(a) (b) (c) (d) (e) (f)

FIGURE 6: Black band noise removal. (a) Original Image. (b) Corrupted by black band noise. (c) Median-filtered image. (d) Lin's adaptive length filter. (e) Gonzalez adaptive length filter. (f) Proposed algorithm.



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

FIGURE 7: (a) Original images, (b) image corrupted by 30% of impulse noise + degradations, (c) DBMF output, (d) Lin's adaptive length filter, (e) Gonzalez adaptive filter, (f) proposed algorithm.



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

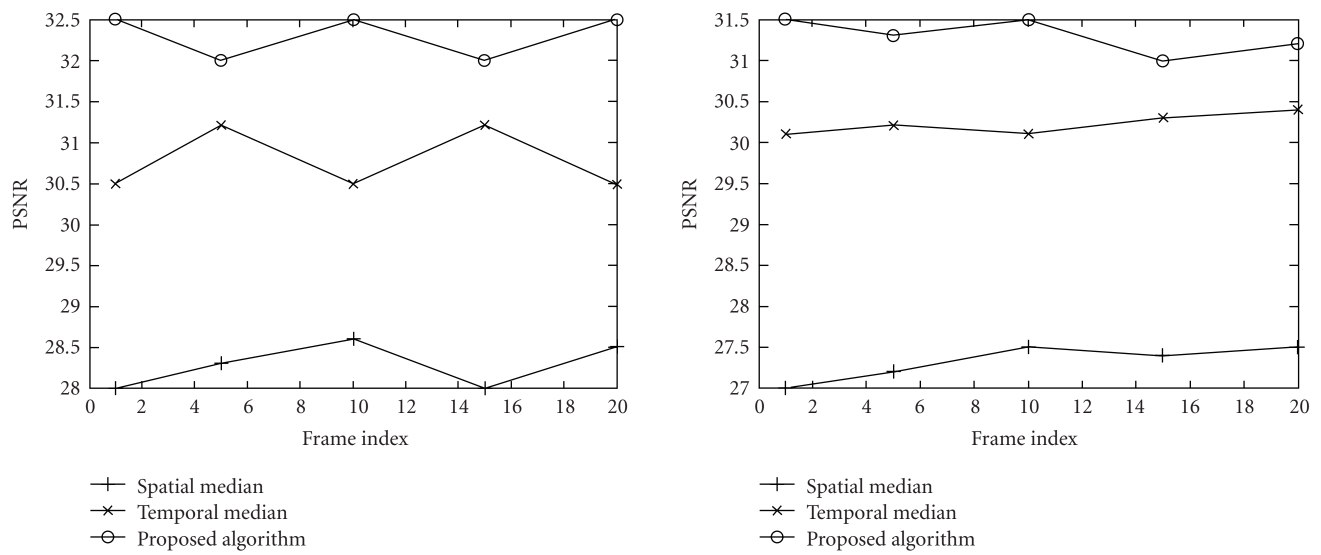
Figure 8: (a) Original images, (b) image corrupted by 70% of impulse noise + degradations, (c) DBMF output, (d) Lin's adaptive length filter, (e) Gonzalez adaptive length filter, (f) proposed algorithm.

(a) (b) (c) (d)

Figure 9: Results: (a) noise (white lines, dark lines) corrupted frames from the black and white film "mannathi mannan," (b) restored frames by using the proposed algorithm, (c) noise (white lines, dark lines) corrupted frames from the Color film "lesa lesa," (d) restored color frames by using the proposed algorithm.

(a) (b) (c) (d)

Figure 10: Results: (a) noise (blotches, impulses) corrupted frames from the black and white film "mannathi mannan," (b) restored frames by using the proposed algorithm, (c) noise (blotches, impulses) corrupted frames from the color film "lesa lesa," (d) restored color frames by using the proposed algorithm.



(a) (b)

Figure 11: (a) PSNR comparison graph of "mannathi mannan" black and white film (b) PSNR comparison graph of "lesa lesa" color film.

Table 2: PSNR, IEF, and MSE for various filters for goldhill.gif image at different noise densities + degradation.

Noise + degradation	PSNR					IEF					MSE				
	SMF	Lin's	AMF	DBMF	PF	SMF	Lin's	AMF	DBMF	PF	SMF	Lin's	AMF	DBMF	PF
0.05	16.21	16.77	17.96	18.78	27.25	3.74	3.57	4.7	5.63	43.79	1308.3	1367	1038.5	859	704.4
0.3	12.82	16.09	17.32	18.48	25.31	2.65	5.3	7.01	9.20	51.61	3232.9	1599	1204.9	921.7	684.6
0.5	10.14	13.48	15.23	18.17	23.84	1.90	3.9	5.84	11.45	46.47	5978.2	2916	1948.7	988.8	657.2
0.7	08.02	09.62	11.20	17.53	22.01	1.41	2.4	2.91	12.47	37.72	10149	7050	4923.2	1148.0	776.1

Table 3: PSNR of Lena and Goldhill image corrupted by 20% of impulse noise and the rproposed algorithm corrupted by 20% noise + degradations.

Filter	Lena	Goldhill
SMF	31.42	29.60
CWMF [12]	30.39	29.87
DBMF [13]	35.12	33.31
Mithra [15]	36.15	34.18
TSMF [14]	31.84	31.53
ACWMF [8]	36.54	34.42
Luo [9][1]Anemia	37.05	36.20
PF (noise + degradations)	35.15	35.05

7. CONCLUSION

An adaptive length median/mean algorithm for removal of drops lines, strip lines, white bands, black bands, blotches, and impulses with minimum of blurring is developed. The performance is evaluated in terms of MSE, PSNR, and IEF. The performance is compared with Lin's adaptive median filter, Gonzalez adaptive median filter, weighted median filter, decision-based median filter and adaptive center weighted median filter. The results show that the algorithm is more effective in the removal of drop lines, strip lines, white bands, black bands, and blotches along with impulse noise varying upto 70%. The advantage of the proposed algorithm is that a single algorithm with improved performance can replace several independent algorithms required for removal of different artifacts. Application of the proposed algorithm to black and color video sequences is also illustrated.

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