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High Density Video Impulse Noise Reduction Scheme Based on Spatially Growing Modified Median Filter

Neeraj Kumar Singh, Arun Kumar Sunaniya

Abstract*: In this paper a spatially growing modified median filter method has been proposed for the restoration of digital videos which are adulterated by the saturated impulse noise i.e., salt-and pepper noise. The proposed denoising process executes filtering action only to the corrupted pixels in the video keeping noise free pixels in the video unharmed. The current study has used a spatially growing window method for the exclusion of high density noise present in the digital videos. It has used sliding window of increasing dimension centered at any pixel and sequentially swapped the noise corrupted pixels by the median value of the trimmed window. However, if the whole pixels in the window are noise corrupted then the dimension of sliding window is enlarged in order to obtained the noise free pixels for median computing. At the same time, this process has been found to be capable to removing the high density salt and pepper noise and also well preserved the fine details of the videos. Experimentally, it has been found that the proposed method generate enhanced PSNR and SSIM results.

Keywords: Spatially Growing, Modified median filter, Impulse noise, Impulse detector, Noise filtering.

I. INTRODUCTION

During the last few decades, digital image processing has evolved as a key technology for the various technological fields such as medical imaging, counting the number of people in a crowd, face recognition etc [12]. Digital images which are essentially 2D sampled data represent the information in terms of the gray value exhibited by the pixels [3]. The gray value of the pixels is determined by the photon counts acquired by the imaging sensor during the process of image acquisition [1]. This process is prone to noise contamination because of the thermal fluctuation or sudden illumination transients. In this paper, we limit our discussion to impulse noise in general and salt and pepper noise in particular. As the name suggests, the most distinguishing feature of salt and pepper noise is its intensity value. Noise infected pixels can acquire either 0 or 255 intensity value in any 8-bit grayscale image [5]. When the noises are non additive in nature, linear filters fall short to reduce the noise present in the image because of the intricate noise distribution in the candidate image. In such situations, non linear filtering strategies are employed for the purpose of noise reduction in the noisy image [4]. Various nonlinear filtering schemes exist for the reconstruction of noise corrupted images infected by the salt and pepper noise [7]. Among such filtering schemes, median filtering scheme holds a prominent place because of its inherent capability to reduce the impulse noises while preserving the image boundaries [8]. It has been reported that SMF (Standard Median Filtering) performs effectively only at the low noise density of contamination [6]. This problem can be overcome by increasing the kernel dimension but large kernel dimensions inevitably blur the fine image details. Such undesirable blurring effect limits the practicability of SMF and its variant (i.e. Adaptive Median Filtering,AMF) [9].

Most of the median filter or its variants operate uniformly on the whole input image without attempting to distinguish between the noise corrupted or noise free pixels [11].Consequently, such schemes perform filtering operation in the noise free pixels that leads to the blurring of the candidate image. To reduce the blurring effect, filtering operation must be employed to noisy pixels only which essentially involve a discrimination mechanism that can identify the noise corrupted pixels present in the image [13]. To fulfill this objective, various schemes were attempted in the past viz. switching median filters. In such filtering schemes, noisy pixels are identified based on some mechanism with a follow up filtering action on the noisy pixels only keeping noise free pixels intact [14]. However, detection mechanism itself comes with a prerequisite of certain pre calibrated threshold values that are used to determine the pixel's nature. Often, it is difficult to define such threshold values because of the various reasons e.g. there can be variety of the objects which are likely to be present in the foreground of the image, candidate image may have a complex background etc. In addition to that, such schemes fail to work efficiently at high noise densities and causes serious distortion to edge details. The proposed two phase algorithm to overcome the above mentioned problems [15]. This approach consisted of an AMF in the first phase for the classification of noisy pixels with a follow up specialized regularized method to restore the detected noisy pixels. This scheme works acceptably in reducing the noise and preserving the image details but poses some problems due to larger processing times because of large kernel dimensions.

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***** Correspondence Author
Neeraj Kumar Singh*, Department of Electronics and Instrumentation Engineering, National Institute of Technology, Silchar , Assam, India.Email:neeraj28sept@gmail.com
Arun Kumar Sunaniya, Department of Electronics and Instrumentation Engineering, National Institute of Technology, Silchar , Assam, India. Email: arun.sunanya@gmail.com

To overcome this drawback, Decision Based Algorithm was proposed. In Decision Based Algorithm [16]. filtering scheme, noise reduction is achieved by using a fixed kernel size of 3×3. When pixel's gray value is equal to either 0 or 255 then it is fed to the filtering unit for the cleaning purpose, otherwise the pixel is left intact [17].

This filtering scheme is ineffective at high noise densities; at high noise densities, the median of the sliding kernel will be either 0 or 255 if kernel consists more number of noisy pixels, compared to noise free pixels. This type of problem was resolved in the MDBA (Modified Decision Based Algorithm) [18] approach in which if the candidate kernel contain pixels with 0 or 255 intensity value only then the restored value for the noisy central pixel could not be calculated. Therefore, this approach does not fits for the noise reduction if the image is corrupted with the high noise density [19].In Decision based coupled window [10] mean filter denoising is performed using windows of larger dimension in order to find more number of noise free pixels.

II. NOISE MODEL

Noise model helps to establish a framework to process the noise infected pixels. Such model attempts to explain the characteristics of noise infected and noise free pixels. Salt and pepper noise model has been taken into account for the present work to design a spatial filter for the cleaning of highly concentrated noise from the infected image [2]. In present model, the probability of existence of salt and pepper noise in any type of image is same. Let $Q1$and $Q2$ be the existence probability for salt and pepper noise in any type of grayscale image $I(i, j)$

Let $X(i, j)$ be the resultant image then,

$X(i, j) = I(i, j)$*with probability* $(1-q)$

Q_1 with *probability* $q/2$ (1)

Q_2 with *probability* $q/2$

Where q is the total probability of existence of noise.

III. PROPOSED SCHEME

Filters which are related to trimming rejects the noise infected pixels from (3×3) window size based upon a previously decided threshold value. Symmetrical trimming filters like alpha mean trimming which trims the pixel values symmetrically from both the ends [10].on the other hand this type of symmetrical operation also cause removal of some portion of non infected pixels which is not important in any type of filtration activities. To control this types of problem unsymmetrical trimming comes into picture. In trimmed median filter i.e unsymmetrical, pixel values are placed in ascending or descending fashion of their intensity magnitude. This process trimmed all 0 and 255 values and then median of the left out pixels from the window is determined. This determined is applied to change the central noise infected pixel values of the working window [18]. But this technique is not productive at high concentrated noise. In the proposed scheme, the stated issues have been sort out by taking windows of step up range for every noise infected pixel values. The proposed Phase of the spatially growing modified median filter method for any type of gray scale videos are as follows. In the first phase of the proposed SGMMF scheme is to specify a window where the scheme works to change the noise corrupted pixels with the pixels without noise. Window choice we consider two dimensional window of form $(2n+1)\times(2n+1)$ say W_n . Assume central pixel under the operation be $I(i, j)$ for W_n sliding window. First considering n = 1 in the algorithm. In the second phase of the proposed scheme is to identify the noise corrupted pixel. For this proposed method we adopt a rule which is given in the Eq.(2).Pixels which was corrupted with Salt and Pepper noise can have only 0 or 255 intensity magnitude. Thats why, this type of noise corrupted pixels will be efficiently determined by comparing the pixel value with 0 and 255. Now for noise corrupted pixel Detection. Whenever $I(i, j)$is 0or 255intensity magnitude, on that occasion it is considered as noise infected pixel [12].This detection operation can be shown as

$K(i, j)$ = Pixel with noise corrupted whenever $I(i,j)$ is 0 or 255

Pixel without noise whenever $0 < I(i, j) < 255$ (2)

Whenever pixels values lies $0 < I(i, j) < 255$ on that occasion $I(i, j)$ value is without noise and left unchanged. In the third phase whenever a pixel is found to be noise corrupted at that time SGMMF method avail the neighboring values of the window which was mention in first phase of the proposed scheme over $I(i, j)$ to work filtration on the central pixel. SGMMF execute filtration by cleaning 0's intensity magnitude and 255's intensity magnitude from the window followed by median computation of the left out pixels. Window of large noise density consist of all noise infected pixel. For such type of operation, the size of the window is enlarged to detect the pixels without noise from the noise corrupted pixel for median estimation. Noise Cleaning operation: whenever $I(i, j)$ is 0 or 255, then trim entire 0's and 255's from the W_n window. Suppose recent cleared trimmed window be TW_n After the execution of trimming operation on on noise corrupted pixels following condition are possible

Condition 1 whenever the sum of constituting component in TW_n are not equal to zero, then the magnitude of $I(i, j)$ is replaced as

$k(i, j) = \{median(TW_n)\}$ (3)

where $k(i, j)$ is the reconstructed magnitude.

Condition 2 whenever the sum of components in TW_n is zero, revise the magnitude of n as

(n less than 5):

$n = n+1$ (4)

And move to phase 1.

Now in the fourth phase dimensional range of the window is enlarged preferably $n < 5$ to detect the pixels which was not infected by the noise. Enlarging the range of the window more than $n \geq 5$ will rise the computational complication of the proposed method. More- over, the calculated median value obtained by fixing $n \geq 5$ was not much correlated with the $I(i, j)$'s locality values. Whenever entire pixels are noise corrupted for n equal to 4, then the SGMMF technique replace the noise corrupted pixel with the mean magnitude of W_1.

If the total of components in TW_4 is zero, substitute $I(i, j)$ as

$k(i, j) = mean(W_1)$ (5)

In fifth phase of the proposed technique Repeat phase one to four in for loop till the entire pixels of the video are executed.

In the case of Multichannel videos the above proposed phases executed independently for every color channel. After finishing the denoising action, channel which are independent are combined to obtained a denoised color video.

IV. EXPERIMENTAL RESULTS

The experimental results of the proposed method has been evaluated and correlated with various types of the standard median based filters. In this work, we have attempted an experiment to determine the impact of the proposed method on the Medium level video processing stage. For this, videos of dimension i.e.,(a) Big Buck Binny, dimension: (512×512×3) and (b) Student, dimension: (512 × 512 × 3) have been considered, with changing noise density, starting from 10% to 70%. Then, these videos were processed through the proposed spatially growing modified median filter approach followed by an Peak Signal to noise Ratio and structural similarity index measure calculation using Equations (5) and (6) respectively.

$$PSNR = 20\log_{10}\left(\frac{255}{\frac{1}{AB}\sum_{i=1}^{A}\sum_{j=1}^{B}\left(X(i,j)-\hat{X}(i,j)\right)^2}\right) \quad (6)$$

$$SSIM\left(X,\hat{X}\right) = \frac{\left(2\mu_X\mu_{\hat{X}}\right)\left(2\sigma_{X\hat{X}}+C_2\right)}{\left(\mu_X^2+\mu_{\hat{X}}^2+C_1\right)\left(\mu_X^2+\mu_{\hat{X}}^2+C_2\right)} \quad (7)$$

Where, $X(i,j)$ and $\hat{X}(i,j)$ represent the noisy image and the restored image, respectively. μ and σ represent the mean and standard deviation from the peak intensity of the image. C_1 and C_2 are the constants respectively. Better results of the proposed method in terms of PSNR and SSIM with the other standard techniques was also verified with the help of the performance graph. For the sake of concision, the performance graphs showing only proposed method for 15 continuous frames of student video, illustrated in Fig 3. Usually denoising methods are an essential components of low level video processing [14]. Hence, for an useful system, denoising techniques should work better to help medium or high level video processing phase. Fig 1 illustrates the visual output for the 15th frame of Big Buck Bunny video corrupted with 30% noise density. Fig 1a is the Noisy image, and Fig 1b-f is the outputs of the various standard filters. Fig 1g is the output of the proposed algorithm

Table I. PSNR (db) and SSIM for various standard video datasets (for 12th frame corrupted with 10% impulse noise) restored with various algorithms

Filter type	Attribute	Big Buck	Foreman	Hall Monitor	students	News	Mother daughter
SMF	PSNR	38.5956	34.55	31.5	31.813	32.3687	37.803
	SSIM	0.9813	0.9362	0.9432	0.9127	0.9602	0.9629
AMF	PSNR	46.1962	36.0419	35.5915	37.1333	35.7363	41.8658
	SSIM	0.9939	0.9785	0.9731	0.9731	0.9853	0.9887
PSMF	PSNR	38.0935	36.357	32.8234	33.9621	32.8433	41.3384
	SSIM	0.9161	0.7954	0.9783	0.9594	0.9215	0.9913
MDBA	PSNR	47.9824	33.0861	29.1559	40.7438	37.4933	32.2199
	SSIM	0.9963	0.9944	0.9914	0.9929	0.9943	0.9861
MDBUTMF	PSNR	49.0959	34.1403	30.6853	42.3921	325272	39.3344
	SSIM	0.9956	0.9783	0.9611	0.993	0.9866	0.9819
Proposed Approach	PSNR	50.4692	35.0245	28.8237	42.4017	32.2822	47.2871
	SSIM	0.9969	0.9946	0.9673	0.9938	0.9857	0.9948

It can be trivially observed in Fig 1b that at higher noise density filter blurs the magnificent video details along with inadequate noise removal. Fig 1e and fig 1f illustrates the filtered video Containing sharper details in comparison with Fig.1b-d for Big Buck Bunny video. Though footprint of the presence of salt and pepper noise can be spot in powerful algorithms like MDBUTMF at high concentrated noise, as illustrated in Fig 1f. Removal of noise adequately without degrading the fine video details as evident from the Fig 1g. Same type of visual output were also obtained for student video, illustrated in Fig 2. Better noise cleaning potential along with fine details preservation of the proposed method compare to other standard median filters like SMF, AMF and PSMF decrease the noise level by blurring the video detail

Table II. PSNR (db) and SSIM for various standard video datasets (for 12th frame corrupted with 30% impulse noise) restored with various algorithms

Filter type	Attribute	Big Buck	Foreman	Hall Monitor	students	News	Mother daughter
SMF	PSNR	27.5881	26.5078	25.8318	26.3566	26.1789	28.3625
	SSIM	0.7673	0.7498	0.7392	0.7198	0.7691	0.7446
AMF	PSNR	41.0433	33.2111	31.3196	33.87	31.784	38.2053
	SSIM	0.9848	0.9656	0.9632	0.953	0.9682	0.9771
PSMF	PSNR	30.8261	29.4001	28.2599	29.4472	28.5335	33.4062
	SSIM	0.8102	0.8634	0.9206	0.8644	0.8059	0.9349
MDBA	PSNR	41.4186	31.8386	28.1422	34.849	32.3129	27.9175
	SSIM	0.9871	0.9748	0.9695	0.9664	0.9737	0.9645
MDBUTMF	PSNR	42.4879	31.044	26.8721	35.9973	30.3267	32.024
	SSIM	0.9873	0.949	0.9276	0.9711	0.9679	0.9696
Proposed Approach	PSNR	44.0269	33.4107	25.5761	36.2804	30.3627	40.9235
	SSIM	0.9914	0.9808	0.9511	0.974	0.9422	0.985

Table III. PSNR (db) and SSIM for various standard video datasets (for 12th frame corrupted with 50% impulse noise) restored with various algorithms.

Filter type	Attribute	Big Buck	Foreman	Hall Monitor	students	News	Mother daughter
SMF	PSNR	19.2365	18.7265	19.0925	19.2574	18.6912	19.8698
	SSIM	0.2666	0.2891	0.2848	0.279	0.3071	0.2346
AMF	PSNR	36.8145	30.8127	28.0172	30.7572	28.2363	34.4218
	SSIM	0.9651	0.9322	0.9259	0.9064	0.9328	0.9502
PSMF	PSNR	24.6935	23.4502	23.1381	23.8942	23.6097	25.2966
	SSIM	0.5849	0.6255	0.6286	0.5827	0.5905	0.5967
MDBA	PSNR	36.2365	29.3955	26.3285	30.9037	28.0735	24.3983
	SSIM	0.9641	0.9388	0.9262	0.9121	0.9313	0.9299
MDBUTMF	PSNR	36.5374	27.5377	23.7879	32.1275	27.9678	27.6185
	SSIM	0.9469	0.8974	0.8272	0.9204	0.916	0.9373
Proposed Approach	PSNR	40.1614	31.9387	26.2523	32.7757	28.4231	37.3065
	SSIM	0.9817	0.959	0.9262	0.9409	0.9497	0.9682

Table IV. PSNR (db) and SSIM for various standard video datasets (for 12th frame corrupted with 70% impulse noise) restored with various algorithms.

Filter type	Attribute	Big Buck	Foreman	Hall Monitor	students	News	Mother daughter
SMF	PSNR	13.7992	13.4469	14.1651	14.1827	13.407	14.666
	SSIM	0.0736	0.0908	0.1048	0.0853	0.1115	0.0633
AMF	PSNR	26.8512	24.4223	23.2933	25.2262	23.4329	26.6239
	SSIM	0.799	0.7348	0.6995	0.7083	0.7383	0.7381
PSMF	PSNR	13.8273	13.4941	14.1765	14.2056	13.6209	14.6748
	SSIM	0.0754	0.0944	0.1095	0.0923	0.1189	0.0667
MDBA	PSNR	30.8152	25.8607	23.513	26.5057	24.1993	23.0646
	SSIM	0.8997	0.8347	0.826	0.7943	0.8312	0.8554
MDBUTMF	PSNR	27.5538	23.4091	20.8947	26.6404	23.778	24.4308
	SSIM	0.6543	0.6414	0.6656	0.6771	0.6074	0.7218
Proposed Approach	PSNR	35.9185	29.7883	24.5426	29.8635	26.3492	34.3227
	SSIM	0.9616	0.9182	0.8834	0.8847	0.9112	0.9398

In order to understand the effect of applying the proposed algorithm on the medium/high level video processing stages [7] we have compared the values of PSNR and SSIM of proposed algorithm with the exisiting salt and pepper denoising methods by changing noise values (10% to 70%) illustrated in the above tables (I-IV) for Big Buck, Foreman, Hall Monitor, Students, News, Mother Daughter videos. We also quantitatively studied the effect of denoising performance of the Spatially growing modified median filter algorithm. By seeing the quantitative values its shows that proposed algorithm behaves better than published median based filters.

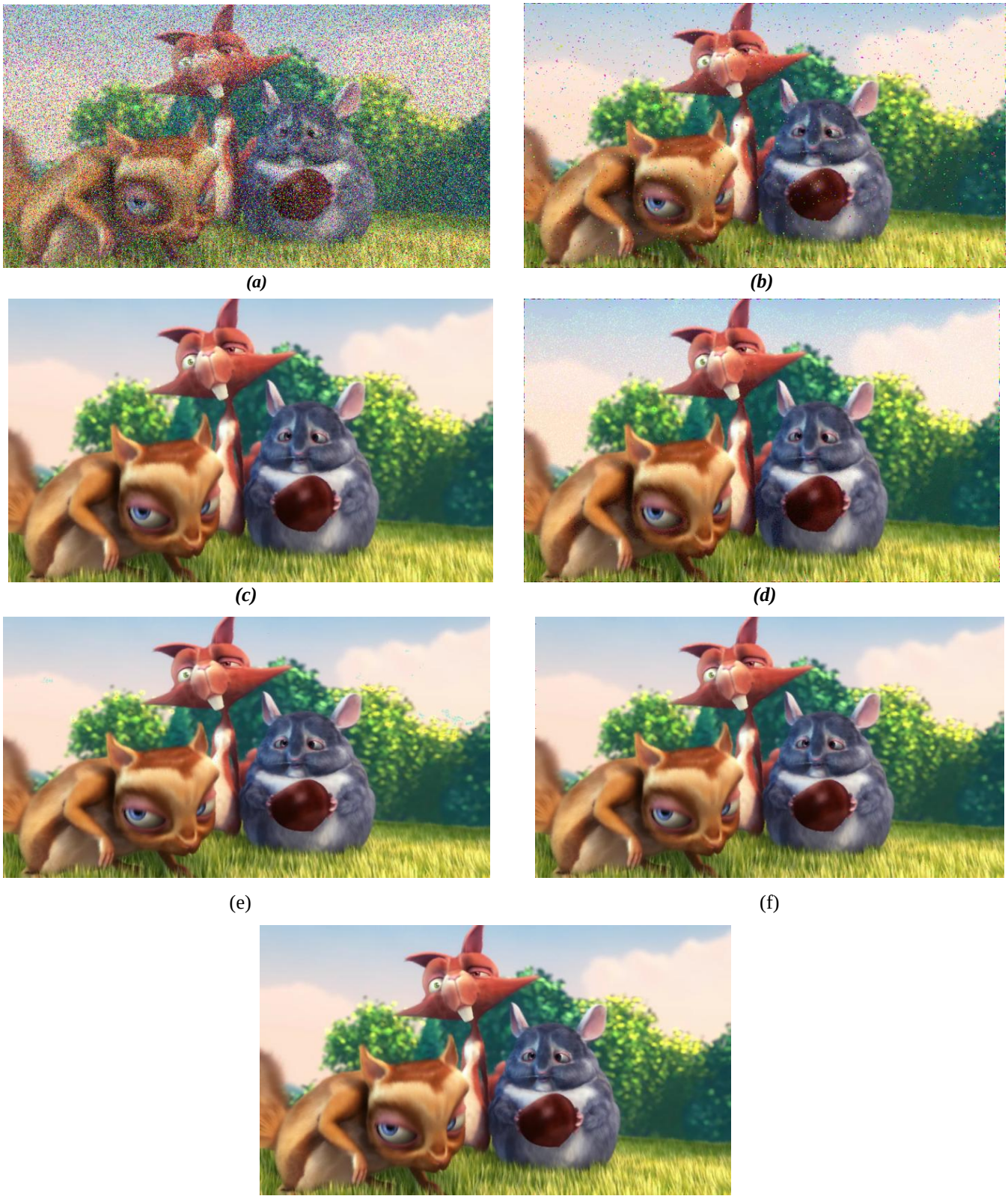


Fig .1. Simulation results of different algorithms for 15th frame of Big Buck Bunny video corrupted with 30% noise density. a Noisy image; b SMF Output; c AMF Output; d PSMF Output; e MDBA Output; f MDBUTMF Output; g SGMMF Output

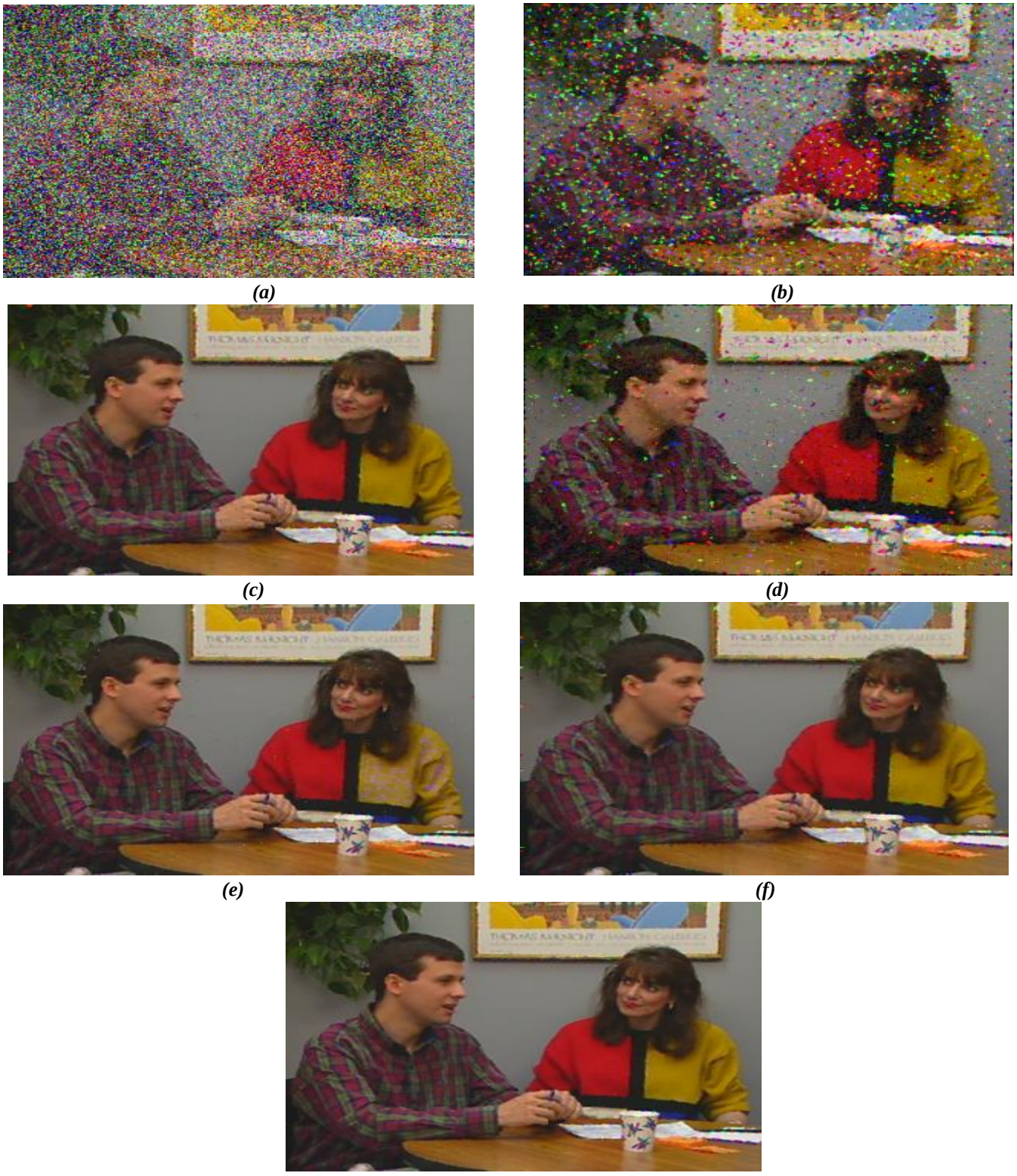
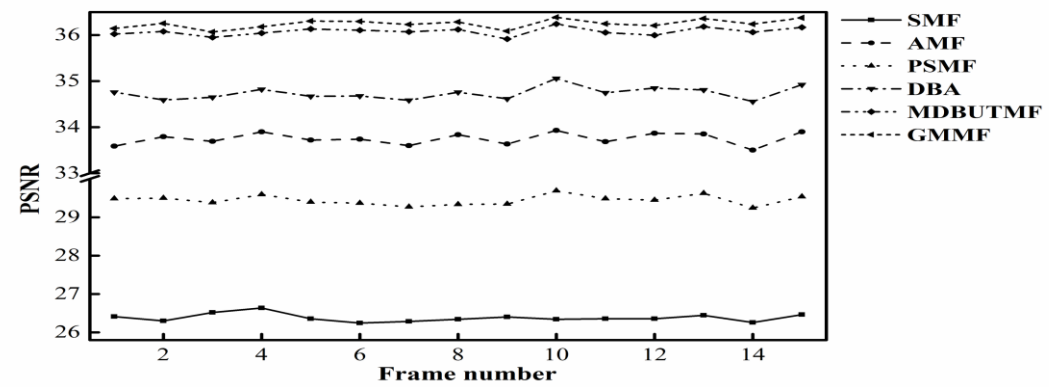


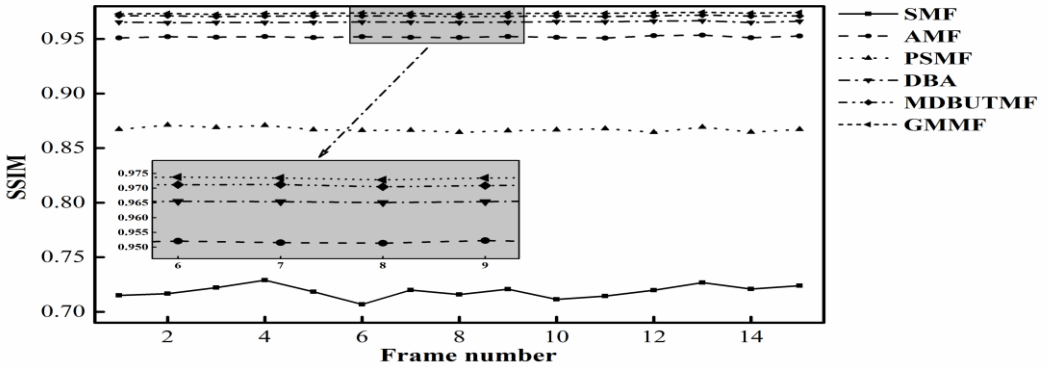
Fig. 2. Simulation results of different algorithms for 30th frame of Students video corrupted with 50% noise density. a Noisy image; b SMF Output; c AMF Output; d PSMF Output; e MDBA Output; f MDBUTMF Output; g SGMMF Output

Proposed method gives better PSNR values as compared to MDBUTMF at lower noise density because of that the proposed method incremented the window dimension for the extraction of pixels from a mixture of pixels and noise if total pixels presented in the window are noise corrupted. MDBUTMF scheme follows an perceptive method to find the average of the noise infected pixel of (3×3) window size in this case [13].

Expanding window size is profitable if all the pixels in the window are noise infected contributing high amount of PSNR and SSIM values. High value of Peak to signal noise ration value is crucial for every video processing phases.Variation of (a) PSNR and (b) SSIM over 15 continuous frames for student dataset is illustrated in Fig.3. From Fig.1g and 2g its clearly seen that the proposed algorithm work better than existing filters in reduction of the noise and preservation of the fine video details from noise corrupted videos



(a)



(b)

Fig. 3. Variation of (a) PSNR and (b) SSIM over continous frames for students dataset.

V. CONCLUSION

In this paper, we proposed an efficient SGMMF method for the reconstruction of videos, infected with high values of salt and pepper noise. The proposed approach works in two modes, i.e.,(1) noisy pixel detection stage and (2) filtering stage. SGMMF method gives comparatively better results at lower noise densities. Incrementing the window size is beneficial for doing denoising at higher noise values, chances of getting a noise free pixel is more. Established test videos Big Buck, Foreman, Hall Monitor, Students, News, and Mother Daughter have been used to calculate the performance of various algorithms. Experimentally, it has been found that the proposed method provide better results in terms of high Peak to Signal Noise Ratio and Structural Similarity Index as compared to other standard filters.

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AUTHORS PROFILE

Neeraj Kumar Singh, Department of Electronics and Instrumentation Engineering, National Institute of Technology, Silchar , Assam, India.

Arun Kumar Sunaniya, Department of Electronics and Instrumentation Engineering, National Institute of Technology, Silchar , Assam, India.