Decision-based Adaptive Proximity Geometric Mean Filter for Removal of Salt and Pepper Noise in Digital Images

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***Abstract*— The noise may introduce in an image during different processing and may cause loss of important information. The denoising has become a crucial step in image processing and demands a highly effective technique that can efficiently eliminate noisy pixels while preserving the essential features of an image. This paper introduces a method for removing salt and pepper (SAP) noise using a Decision-based Adaptive Proximity Geometric Mean Filter (DAPGMF). The DAPGMF effectively denoises images corrupted with a wide range of noise densities. The primary focus of the algorithm is to denoise high-density ($>80\%$) SAP noise-corrupted images. The proposed approach considers proximity pixels and adaptively increases the window size depending on the minimum number of noise-free pixels required in the current window. Additionally, the algorithm incorporates the concept of previously processed pixels and the mean of the pixel values in the processing window to handle noisy pixels that were not denoised successfully prior step. The proposed DAPGMF algorithm is contrasted with existing algorithms from recent literature, and extensive experiments are conducted with standard Kodak images. The results demonstrate that the proposed algorithm provides excellent noise suppression and achieves a high PSNR of 23dB and SSIM of 0.65, even at a high noise density ($\geq 90\%$).**

***Index Terms*— Filtering; Salt and Pepper Noise; Geometric Mean filter; Non-linear filter; Noisy Pixel; Noise Free Pixel; Image denoising; Previously Processed Pixel**

I. Introduction

Digital images are often affected by impulse noise. These noises are caused by faulty memory chips, electromagnetic interference, synchronization in digital recordings, timing errors in analog-to-digital converters, and faulty pixel sensors [1]. Impact noise can be divided into two groups: Salt and Pepper (SAP) noise and random value impulsive noise. Salt and Pepper Noise (SPN) is a type of impulsive noise that causes certain pixels of the image to be at their maximum (*i.e.* 255 for 8-bit) or minimum (*i.e.* 0 for 8-bit). When noise is high, the image loses information and visual quality is poor. Many linear and non-linear filter approaches have been developed to eliminate SPN while preserving the edges. These techniques can only be used at low noise density (ND) levels.

In a standard median filter (SMF) when noisy pixels are detected, the median of a window centered at the candidate corrupted pixels is computed [2]. Because SMF fails to denoise images at high noise density, numerous versions of median filtering, particularly adaptive and switching filtering, have been designed. Adaptive Median Filter (AMF) [3] uses shifting window sizes to provide noise-free pixels (NFPs), outperforming SMF. Large window size induces visual blurring at high noise density. Because of this limitation, the Decision-Based Algorithm (DBA) [4] was devised, which uses the rapid switching concept and orders pixels in a 5×5 window. Even yet, at high noise density ($ND \geq 60\%$), it generates undesirable streaking effects. In addition, various linear and non-linear filtering techniques are proposed [5], which are effective up to a certain noise density limit but lose edge details and lead to image blurring beyond a limit. As an outcome, high noise density SAP noise still needs to be handled, which necessitates the use of an efficient filter. This study presents a decision-based adaptive proximity geometric mean filter for removing high-density noise ($>90\%$). The major contributions of the paper are as follows:

1) The presents a comprehensive comparative analysis of the state-of-the-art filtering techniques.
2) A novel Decision-based Adaptive Proximity Geometric Mean Filter (DAPGMF) to effectively eliminate the SAP noise over the wide range of noise density.
3) A comparative performance analysis of the proposed DAPGMF over the existing filtering techniques using Kodak benchmark images is presented.

The paper is divided into the following sections. Section II is a literature survey, while Section III includes the proposed algorithm and an example depicting the working of the suggested algorithm at medium and high noise densities on Lena image, while Section IV presents the simulation results and its analysis whereas, Section V conclude the work.

II. Literature Survey

Numerous filtering methods, including median, interpolation, weighted mean, and convolution, are presented in the literature to reduce impulsive noise while retaining visual data. The switching median filter functions effectively only at very low noise density ($ND < 30\%$). At increasing noise densities, the window of larger size is taken where the blurring effect begins to predominate, but it is necessary to compute the median as a noise-free pixel for that window. Because of this drawback, a Decision-Based Median Filter (DBAMF) [6] was proposed. In this filter, a 3×3 window is taken and sorted in a certain way (row-wise, column-wise, and diagonally) so that the median is the middle pixel of the resulting matrix. This middle pixel is used for restoring the noisy pixel (NP). If the middle pixel remains noisy, the closest NFP is used to restore the NP. The median of this filter typically turns out to be noisy at large noise densities, as a result, the same pixel repeats, creating a streaking effect. To enhance the DBAMF's performance, an unsymmetric trimmed median filter (UTMF) [7] is presented where the candidate pixel is restored by the median of the NFPs in a 3×3 window.

To improve the performance further, a Modified Decision-Based UTMF (MDBUTMF) [8] is presented that takes the mean value of all noisy pixels if none NFPs are present in the current window otherwise takes the median of the NFPs to denoise the candidate noisy pixel. The MDBUTMF fails when there is a lot of noise because every pixel in the local window is noisy. An adaptive weighted mean filter (AWMF) is suggested as a result of these shortcomings. The AWMF [9] gradually increases the window size until the maximum and minimum values of two successive windows are identical and there is at least one pixel between the local minimum and maximum. Compared to AMF, the AWMF denoises better but occasionally makes mistakes when recognizing noisy pixels at low noise density.

Simple Adaptive Median Filtering (SAMF) [10] is an adaptive-switched-trimmed median filter in which an estimation is made using NFPs that are present in that adaptive window in place of a noisy sample. Despite having good denoising results in terms of quantitative metrics such as PSNR and SSIM, SAMF cannot recover the information present in images with high noise densities. In order to remove SPN, a distinct applied median filter (DAMF) [11] is proposed that takes neighboring pixels into account and uses an adaptive window. Cloud Model Filter (CMF), uses a cloud model for the detection step, [12]. It takes advantage of the randomness and fuzziness in impulse noise. In the filtering stage, a weighted fuzzy mean filter is employed. At greater noise densities, the CMF successfully detects SAP noise with a total misclassification rate of $< 0.01\%$. However, at lower noise densities, its detection rate marginally declines.

Another technique that provides better restoration of noisy pixels while maintaining computational efficiency is the Interpolation-Based Impulse Noise Removal (IBINR) technique [13]. The IBINR restores the candidate noisy pixel with a weighted mean of uncorrupted pixels where the weights are based on their Euclidean distance from the center. On the other hand, an improved tolerance-based selective arithmetic mean filtering technique (ITSAMFT) [14] filter detects ND and if it exceeds a threshold, replaces noisy pixels by the mean of the current window (CW) or leaves them unaltered. The filter fails at high ND due to a lack of original pixels. To achieve high image quality at high ND, Probabilistic Decision Based Median (PDBM) [15] filter is presented. Depending on the ND, the PDBM denoises the noisy pixel using either a trimmed median or a patch median. The most recurrent NFP among the uncorrupted neighboring pixels of the noisy pixel is set as the new value in a recently introduced method based on pixel density (BPDM) [16]. This approach first determines if the current pixel is NP or NFP. This filtering approach fails badly when the ND is very high (≥90%).

To address this problem a Fast Switching Based Median-Mean Filter (FSBMMF) [17] was proposed which has two stages: detection and filtering. In the detection stage, noisy pixels are identified. Subsequently, in the filtering stage, each corrupted pixel is replaced by the mean/median of the trimmed window. If no noise-free pixel is present then the corrupted pixel is replaced by a previously processed pixel. This has been illustrated by Eq. (1), where, $median^{3\times3}$, $median^{5\times5}$, $mean^{3\times3}$, and PPP represent median operation on a 3×3 and 5×5 window, mean operation with 3×3 window, and the Previously Processed Pixel (PPP) operation, respectively. The PPP is the most recently denoised pixel value.

$$O(p_{i,j}) = \begin{cases} median^{3\times3}(p_{i,j}) & \text{if, noise-free pixel} \\ median^{5\times5}(p_{i,j}) & \text{if, noise-free pixel} \\ mean^{3\times3}(p_{i,j}) & \text{if, non-boundary pixel} \\ PPP(p_{i,j}) & \text{else, PPP} \end{cases} \tag{1}$$

To further reduce computation time, a Fast Adaptive High-Performance Filter (FAHPF) [18] was developed which used a three-stage process: overlapping medians, running averages, and 3×3 mean for the denoising process. The overlapped median (OM) output is given by Eq. (2) where $\dot{m}_w$ is the complement of m_w, (&) is the pixel-wise AND operation, and (.) indicates pixel-wise multiplication. Recently, an Improved Fast Median Algorithm (IAMFA-I and IAMFA-II) [19] was also proposed which replaces the noisy pixel by using a median-based sliding window technique which is a time-efficient algorithm with appreciable results.

$$\begin{aligned} OM = {} & F_1.m_1 + F_3.(\dot{m}_1 \& m_3) \\ & + F_5.(\dot{m}_1 \& \dot{m}_3 \& m_5) + ... \\ & + F_s.(\dot{m}_1 \& \dot{m}_3 ... \& \dot{m}_{s-2} \& m_s) \end{aligned} \tag{2}$$

Two highly correlated groups of noise-free pixels are produced by an Adaptive Minimum-Maximum value-based Weighted Median (AMMWM) [20] filter using the minimum and maximum values of the current window. The estimated value of a candidate NP is further determined by the weighted medians of these groups. The size of the window is expanded by one if the current one cannot provide any NFPs. To reduce blurring, a window's maximum size of 7×7 is taken into account. Further, a Significance Driven Inverse Distance Weighted (SDIDW) [21] filtering technique is proposed for the removal of impulse noise. Using the fewest possible NFPs, the SDIDW filter restores the noisy pixel. This filter emphasizes the nearest NFPs of a small squared distance to restore noisy pixels this reduces the time complexity of the algorithm. Comparatively speaking, this filter offers superior image quality than other median filters.

Algorithm 1: Proposed DAPGMF(ImgN,OImg)

Function *DAPGMF()* **is**
- **Input** ImgN
- **Output** OImg
- **foreach** *noisy pixel i* $P^n_i,_j$ *of ImgN* **do**
  - ***Initialize*** *k<-1,t<-1*
  - *θ=[1,2,4,5,8,9,10,13,18, ⋯] squared distance till 7X7*
  - **foreach** *k<=9* **do**
    - ***Initialize*** $\hat{\delta}$ *<-[]*
    - ***if***$(\theta(k)==4 \;||\; \theta(k)==9)$ *then*
    - ***increment*** *t*
  - ***Compute*** w^n *centered at i* $P^n_{i,j}$ $//Take w^n_3 x3$
  - **foreach** $\bar{\delta}$ *i* $P^n_{i,j}$ *in* $w^n_{2(t+1)\times 2(t+1)}$ **do**
    - **if** $d(k) \geq (m\text{-}t\text{-}1)^2 + (n-t-1)^2$ **then**
      - **if** *pixel is* $\hat{\delta}$ **then**
        - $\hat{\delta}$ *(end+1)=*w^n
  - **if** *length(* $\hat{\delta}$ *) < 2* **then**
    - ***increment*** *k*
  - **if** *k>9* **then**
    - **if** *length(* $\hat{\delta}$ *)==1* **then**
      - *OImg[i][j]<-* $\hat{\delta}$ *(1)*
    - **else**
      - ***Compute*** *PreviouslyProcessedPixel*
  - **else**
    - ***Initialise*** *mul <-1*
    - **foreach** $\hat{\delta}$ *in* w^n **do**
      - *mul<-mul*(* $\hat{\delta}$ *(* $\hat{\delta}$ *in* w^n*))*
    - ***Compute*** *Geometric Mean OImg[i][j])=round(Gmean)*

Algorithm 2: Previously Processed Pixel

Function *PreviouslyProcessedPixel()* **is**
- **if** *col > 4* **then**
  - **if** *OImg[i-1][j] is* $\hat{\delta}$ **then**
    - OImg[i][j]<-OImg[i-1][j])
  - **else**
    - OImg[i][j]<-mean(mean(w^n))
- **else**
  - **if** *OImg[i][j-1] is noisefree* **then**
    - OImg[i][j]<-OImg[i][j-1]
  - **else**
    - OImg[i][j])<-mean(mean(w^n))

III. PROPOSED ALGORITHM

This section first presents the main algorithm for the Decision-based Adaptive Proximity Geometric Mean Filter (DAPGMF) followed by its complete flowchart and a detailed example depicting the results of the proposed algorithm on images with low, medium, and high noise densities.

A. Noise Model

Let us consider an image $\delta_{[i][j]}$. The SAP noise is represented by the two extreme values of a pixel, *i.e.*, 255 and 0 also represented as $\bar{\delta}$ [0, 255]. A noise vector ($\bar{\delta}$) containing all the pixels including these extreme pixels is considered where the probability of each element is equal. Each pixel in the image is considered as either NP ($\bar{\delta}$) or NFP ($\hat{\delta}$). Only $\bar{\delta}$ is subjected to the filtering process while the $\hat{\delta}$ is left unaffected.

B. Main Algorithm

The proposed filtering technique initially takes into account only a small subset of the nearby pixels while calculating the estimated value of $\bar{\delta}$ to reduce the computational complexity. A few nearest pixels in the window size of 3×3 (with small squared distances (θ)) are taken into consideration and verified whether the pixel is $\bar{\delta}$ or $\hat{\delta}$. Initially, the four nearest pixels with the smallest θ equal to 1 are taken into account. If a sufficient number of $\hat{\delta}$ (in the example we considered this number as 2) are obtained then filtering is done with the help of only these $\hat{\delta}$ pixels. If the number of $\hat{\delta}$ is small, more nearest pixels with θ equals 2 are considered. If sufficient $\hat{\delta}$ are not found within the 3×3 window then exactly the same process is applied in the window of extended size. Generalizing the above in terms of K, initially, a small window is considered $w_{(2K+1)(2K+1)}$ with window size parameter (K) equal to 1. If the number of $\hat{\delta}$ is smaller than the threshold ($\varnothing$), the value of K is increased by 1. In the proposed algorithm, the maximum value of K considered is 3 as the filtered image faces a blurring effect with an increase in window size.

height 0.4pt depth 0pt width .5em

This trend followed by the distances will be as $\theta = [1, 2, 4, 5, 8, 9, 10, 13, 18, \cdots]$. In the proposed algorithm, the computational complexity which is examined in the following part is significantly reduced since it considers fewer closest pixels. If the number of $\hat{\delta}$ is more than the $\varnothing$, the result is obtained from the given formula which will replace the noisy pixel. There may be some cases at high ND where the number of $\hat{\delta}$ at maximum window size is not sufficient and to overcome this problem additional steps are followed by this algorithm which is as if $\hat{\delta}$ is less than the $\varnothing$ value (*i.e.* only one noise-free pixel is present), then replace the $\bar{\delta}$ with the one $\hat{\delta}$ directly. If there is no noise-free pixel in the given window, the previously processed pixel replaces the $\bar{\delta}$. But at high ND, there are chances that the previously processed pixel is also noisy then the direct mean of the max window (7×7) is taken. The example as shown in Fig. 2 demonstrates different

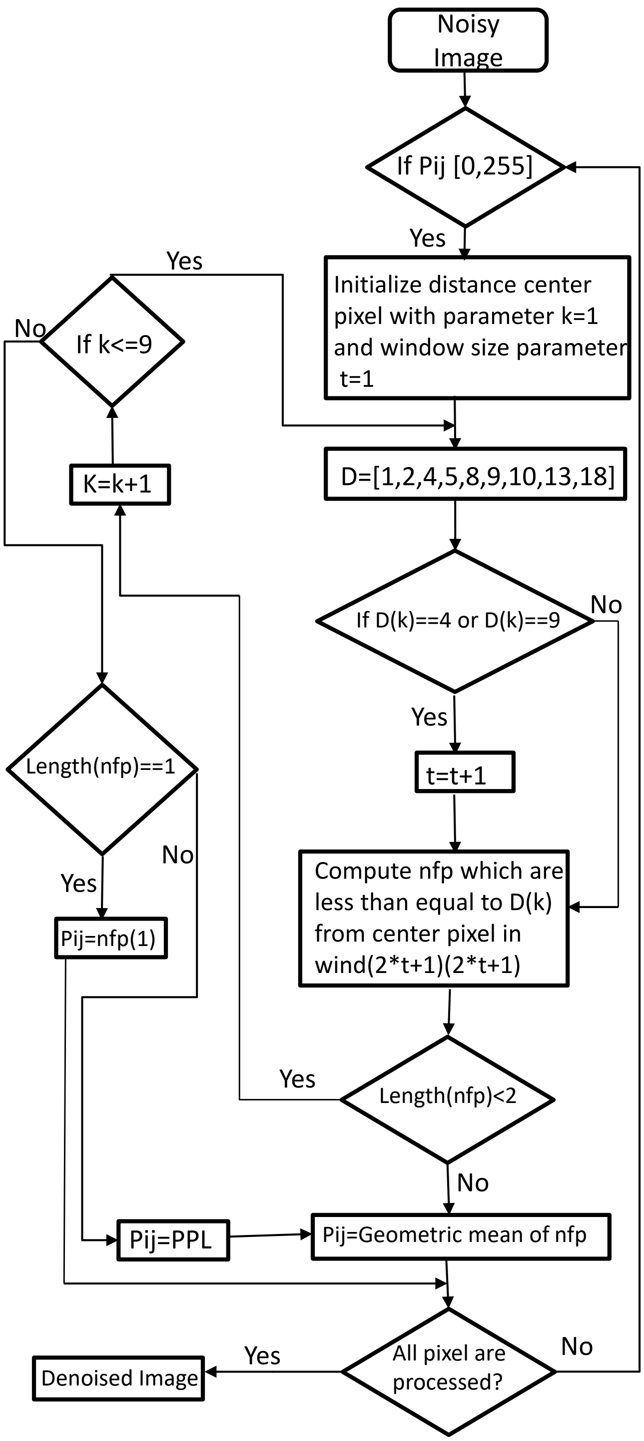

Fig. 1. The flowchart of proposed DAPGMF Algorithm

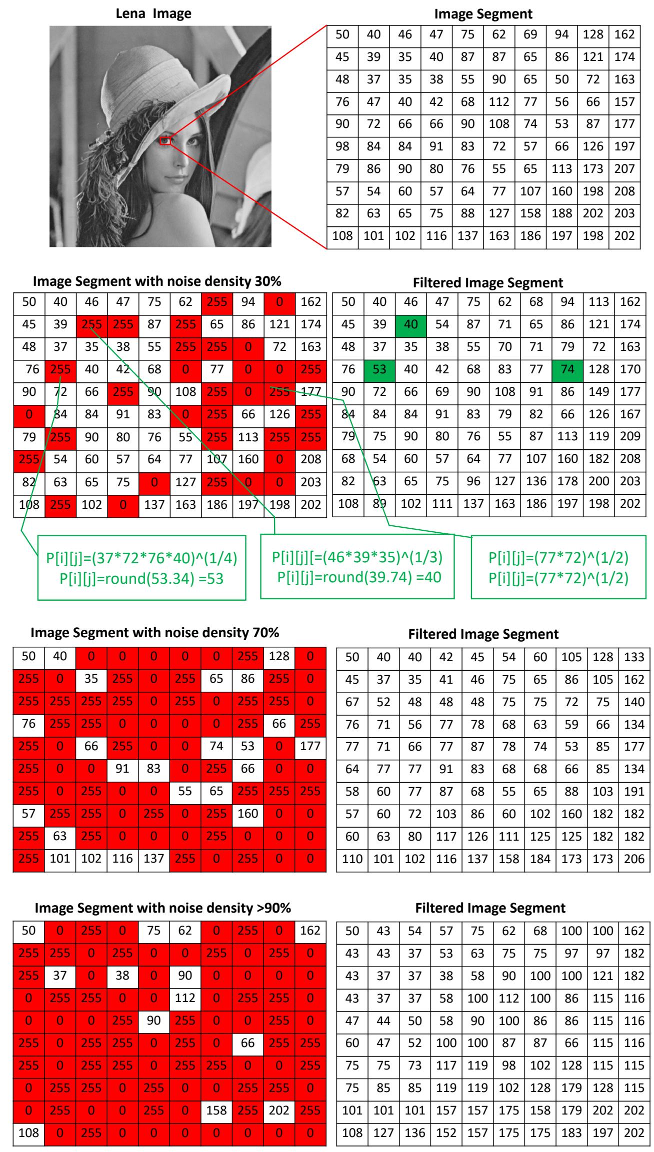

Fig. 2. Illustration of the proposed algorithm using an example.

steps of the proposed algorithm for better understanding. In the figure, noisy images with low ($ND = 30\%$), medium ($ND = 60\%$), and high ($ND = 90\%$) noise densities range are considered and corresponding denoised images using the proposed approach are illustrated.

IV. Simulation Results and Analysis

This section first introduces various performance metrics followed by a discussion on simulation results. The Kodak benchmark images are considered where the SAP noise of varying densities is introduced and are then filtered by proposed and existing filters. The frequently used error metrics such as mean square error (MSE), peak signal-to-noise ratio (PSNR), and structural similarity metrics (SSIM) are evaluated and compared.

The quality metrics PSNR and SSIM values for the proposed and existing filtering techniques using Kodak dataset are shown in Tables IV and Tables IV at the ND equal to 90%. The results demonstrate that the proposed algorithm performs exceptionally well, even at high noise densities, providing higher PSNR and SSIM values than existing filters. Additionally, Fig. IV and Fig. IV depict a plot of PSNR and SSIM for varying noise density using

TABLE I

COMPARISONS OF PSNR OF VARIOUS ALGORITHMS ON KODAK DATASET OF IMAGES AT HIGH NOISE DENSITY ($ND = 90\%$)

Images	DBAMF	MDBUTM	DAMF	BPDM	CMF	PDBM	UTMF	AMMWM	DAPGMF
Img1	21.6454	16.6780	16.6194	10.6516	6.8424	9.3242	20.6387	23.2937	24.7310
Img2	20.5756	15.1707	15.1291	11.1125	6.4867	10.8281	20.2133	22.3707	23.1676
Img3	22.6584	15.0149	14.9676	9.2865	6.4027	7.2691	20.0511	23.4679	25.5617
Img4	17.0596	14.3666	14.3310	10.0599	6.4315	9.4704	16.7742	18.3055	18.6902
Img5	19.7567	14.7799	14.7410	10.9639	6.3924	10.5888	19.3613	21.6426	22.7333
Img6	17.9149	12.5872	12.5633	8.9851	5.6875	8.5407	17.4798	20.4185	22.6838
Img7	24.0352	15.7059	15.6533	10.9948	6.6205	10.2285	22.8660	25.0903	25.9407
Img8	21.7146	13.9254	13.9138	11.0871	6.1268	11.4685	20.9165	23.6365	25.3899
Img9	19.1170	13.9322	13.9088	11.0794	6.1536	12.0109	19.8675	21.7748	22.0469
Img10	19.0620	15.5859	15.5749	10.7323	6.6219	9.4884	19.2163	21.4303	21.9951
Img11	18.4159	15.8098	15.7607	10.9463	6.7485	9.8968	18.6275	20.1952	20.2758
Img12	20.8556	10.4827	10.4813	4.2092	5.1665	4.6871	16.3668	17.8801	16.6137
Img13	20.3449	15.9909	15.9456	10.6039	6.7088	9.5641	18.8054	21.1408	22.3883
Img14	21.7852	16.2244	16.1843	10.9393	6.7349	9.8175	21.9701	24.0961	24.6348
Img15	22.3110	15.7350	15.6797	10.7178	6.6185	9.8197	22.9742	25.5588	26.7461
Img16	16.6387	14.0542	14.0736	9.0803	6.3934	8.6638	18.0470	19.6826	18.9255
Img17	25.1519	15.5356	15.4910	11.5280	6.5553	12.3140	25.1413	26.9288	27.4020
Img18	23.2774	16.0613	16.0065	11.1027	6.6799	10.4704	23.3732	26.1513	27.3353
Img19	22.6945	15.9574	15.9092	11.2034	6.6522	10.7697	22.4950	25.0477	26.4443
Img20	16.5158	13.7970	13.7670	10.8126	6.1503	11.0846	16.8216	18.7977	19.6950
Img21	20.6284	14.4913	14.4566	8.9650	6.3506	8.2263	18.5450	21.0609	22.0178
Img22	21.2512	16.5400	16.4843	11.0726	6.8071	10.0448	20.4316	22.6906	24.6580
Img23	14.4783	13.5609	13.5336	9.5913	6.2051	8.3520	4.7126	16.6379	17.2653
Img24	21.2344	16.8961	16.8311	10.6205	6.8808	8.8542	20.9820	23.4299	24.6497

TABLE II

COMPARISONS OF SSIM OF VARIOUS ALGORITHMS ON KODAK DATASET OF IMAGES AT HIGH NOISE DENSITY ($ND = 90\%$)

Images	DBAMF	MDBUTM	DAMF	BPDM	CMF	PDBM	UTMF	AMMWM	DAPGMF(PA)
Img1	0.6193	0.1656	0.1631	0.0372	0.0126	0.0364	0.6235	0.7058	0.7442
Img2	0.5400	0.1529	0.1501	0.0436	0.0108	0.0602	0.5187	0.6027	0.6264
Img3	0.6764	0.1236	0.1207	0.0349	0.0119	0.0256	0.6560	0.7232	0.7458
Img4	0.3237	0.1833	0.1810	0.0553	0.0202	0.0700	0.3068	0.3876	0.4155
Img5	0.4510	0.1695	0.1681	0.0528	0.0131	0.0698	0.4325	0.5376	0.5890
Img6	0.5955	0.0901	0.0885	0.0389	0.0117	0.0575	0.6541	0.7290	0.7482
Img7	0.6183	0.1315	0.1298	0.0341	0.0091	0.0388	0.5819	0.6468	0.6697
Img8	0.5706	0.1327	0.1326	0.0420	0.0087	0.0720	0.5840	0.6942	0.7486
Img9	0.4223	0.1411	0.1401	0.0470	0.0134	0.0768	0.4839	0.5697	0.5954
Img10	0.5467	0.1607	0.1608	0.0476	0.0128	0.0483	0.5581	0.6323	0.6553
Img11	0.3994	0.2012	0.1984	0.0610	0.0174	0.0670	0.3688	0.4541	0.4723
Img12	0.7185	0.0890	0.0868	0.0266	0.0124	0.0364	0.6256	0.7036	0.7008
Img13	0.6220	0.1744	0.1728	0.0457	0.0143	0.0524	0.5762	0.6461	0.6852
Img14	0.5152	0.1542	0.1527	0.0385	0.0110	0.0402	0.5556	0.6343	0.6475
Img15	0.6750	0.1283	0.1263	0.0320	0.0106	0.0320	0.7487	0.8230	0.8440
Img16	0.4098	0.1656	0.1660	0.0411	0.0127	0.0515	0.4736	0.5746	0.5847
Img17	0.6355	0.1075	0.1057	0.0310	0.0087	0.0404	0.6901	0.7248	0.7159
Img18	0.6764	0.1364	0.1340	0.0335	0.0103	0.0358	0.7196	0.7816	0.7950
Img19	0.5587	0.1429	0.1408	0.0371	0.0109	0.0423	0.6212	0.7055	0.7262
Img20	0.3168	0.1949	0.1931	0.0728	0.0215	0.1056	0.3828	0.4892	0.5456
Img21	0.5454	0.1540	0.1514	0.0422	0.0145	0.0462	0.4716	0.5418	0.5770
Img22	0.6235	0.1918	0.1894	0.0531	0.0153	0.0586	0.5855	0.6896	0.7731
Img23	0.3419	0.2043	0.2024	0.0634	0.0278	0.0780	0.3229	0.4324	0.4827
Img24	0.6687	0.1685	0.1655	0.0406	0.0132	0.0357	0.6670	0.7371	0.7678

the Lena image, respectively.

Fig. 3 depicts the qualitative comparison of the proposed algorithm compared to existing at different ND on the Lena image. The first row displays the processed image using the DBAMF filter at ND ranging from 10% to 90%. The subsequent rows display the processed images for MDBUTM, CMF, BPDM, UTMF, AMMWM, DAMF, Novel MDBF, followed by the proposed algorithm. The figure shows that the quality of the restored image using the proposed algorithm is superior to that of the restored

Fig. 3. Restored Lena image via (a) DBAMF, (b) MDBUTM (c) CMF, (d) BPDM, (e) UTMF, (f) AWMWM, (g) DAMF, (h) MDBF and (i) Proposed filter.

image using existing algorithms.

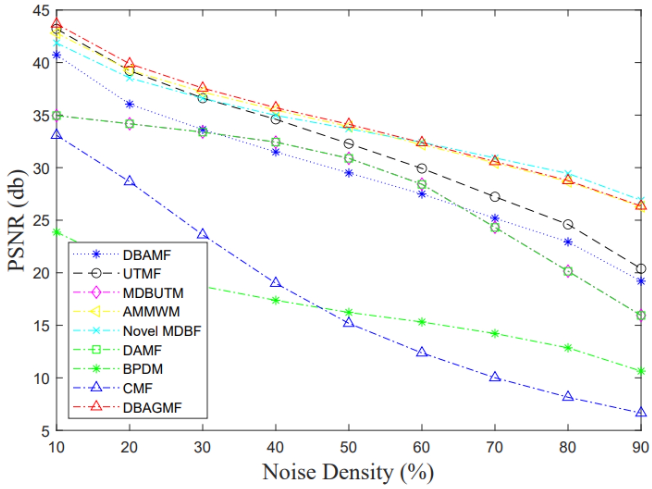

Fig. 4. PSNR values of different algorithms at varying noise density.

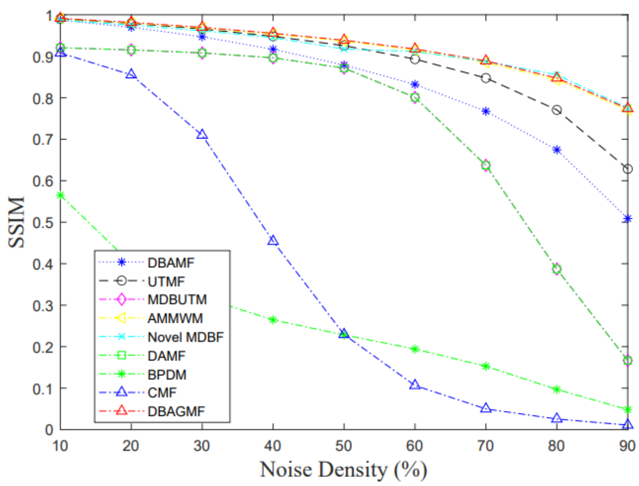

Fig. 5. SSIM values of different algorithms at varying noise density.

V. CONCLUSIONS

In this paper, a decision-based adaptive proximity geometric mean filter is proposed as an effective method for denoising images while preserving image features, even at high noise densities. The filter considers proximity pixels, starting with the closest ones, and if the number of NFPs in the proximity is below a certain threshold, the distance is increased, and the window size is adjusted accordingly. If a replaced value is also noisy, the proposed filter calculates the geometric mean for the NFPs obtained in the proximity and the mean for the processing window. The quality analysis on Kodak images showed that, on average, the proposed filter provides $40db$ and 0.99 higher values of PSNR and SSIM, respectively, for a wide ND range of (10% - 90%). While it provides $26.2db$ and 0.85 higher values of PSNR and SSIM, respectively, for a very high ND range of (91% - 98%) compared to the best-known algorithm.

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