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Simplified Enhanced Median Filter (SEmF) to Reduce the Effects of Salt and Pepper Noise

Ibrahim AL ADWAN
Al-Balqa Applied University, 15008 Amman 11134 Jordan
Tel.: +9622798500795, fax: (+962 6) 4790350
E-mail: Ibrahim.aladwan@bau.edu.jo

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Abstract: This article introduces a new digital filter; this filter will be used to replace the existing standard median filter and the standard average filter. Each possible noisy pixel in the image will be replaced by the median of the selected window, if this median is greater than zero and less than 255, so the possible noisy pixels will be treated leaving the other clear pixel without changes, unlike the median filter, which replace all pixels (clean pixels and possible noisy pixels) with the median of the window. The presented SEmF digital filter will be able to process the gray images and the color images, each color image channel will be treated separately. The presented SEmF will accept a window with any size, and using this window each possible noisy pixel will be treated. The presented SEmF will be implemented using various images affected by various in ratios salt and pepper noise, the obtained experimental results will be compared with the results of standard median and average filters to show how the presented filter will reduce the effect of salt and pepper noise by reducing the noise ratio.

Keywords: Clear pixel, Possible noisy pixel, Salt and pepper noise, Image binary matrix, Median filter, Average filter.

1. Introduction

Various images such as medical-images, satellite-images and astronomical-images can be acquired thanks to the development of technology [1]. During the image acquisition and image transferring some corruption called noise may occur [2]. There are various noise types such as Gaussian-noise, additive-noise and impulse-noise [3]. One of the most frequently occurring degradations in the practical imaging system for digital images acquired, transmitted or stored is the Salt-and-Pepper Noise' (SPN), also known as the fixed valued impulse noise [4]. It is defined by the random changing of intensities of original pixel intensities with either the minimum or maximum gray-level values (usually 0 or 255 for 8-bit images) the number of affected pixels will be called the noise ratio (NR), and increasing the NR will increase the damaged degree in the image [5]. These noises may be caused by faulty camera sensors, errors in analog to digital conversion, malfunctioning memory components, transmission channel noise or errors that are generated when the image is taken or sent [6]. The presence of SPN substantially reduces image quality and has a negative impact on the subsequent image processing tasks such as segmentation, feature extraction, object recognition, medical diagnosis, remote sensing analysis, and machine vision. Thus, the suppression of impulse noise and at the same time the preservation of image details is a basic problem in digital image processing [7]. Image denoising has thus become an essential preprocessing step in many scientific and engineering applications [8]. In the literature, many denoising methods have been proposed, in [9] the authors introduced the Adaptive Median Filter (AMF), which dynamically adjusts the filtering window according to local image statistics. Rather than using a fixed neighborhood for all pixels, the adaptive median filter progressively enlarges the window until a reliable median value is obtained or a predefined maximum window size is reached. This adaptive mechanism

significantly improves restoration performance under moderate and relatively high impulse-noise densities while reducing unnecessary smoothing in homogeneous image regions. Nevertheless, increasing the window size also increases computational complexity and may still produce inaccurate estimates when the majority of pixels within the local neighborhood are corrupted. These limitations motivated the development of more sophisticated adaptive denoising strategies. It is found that the state-of-the-art switching type median filters are mostly nonadaptive to noise density variations and fail to classify the characteristic of the pixel at the interfaces with high density noises. This shows the importance of an adaptive weighted median filter and complex switching schemes. In [10] A median filter with switching-based incorporating the fuzzy-set concept, called the Noise Adaptive Soft Switching Median (NASM) filter is proposed to achieve better improved filtering performance in terms of effectiveness in removing impulse noise while preserving signal details and robustness in combating noise density variations. The proposed NASM filter has two stages. A soft-switching noise-detection scheme was developed to classify each pixel to be uncorrupted pixel, isolated impulse noise, non-isolated impulse noise or image object's edge pixel.

The respective characteristic type identified will then be used with a "no filtering" (or identity filter), Standard Median (SM) filter or the developed Fuzzy Weighted Median (FWM) filter. Experimental results showed that the NASM filter impressively outperforms other techniques by achieving fairly close performance to that of ideal-switching median filter across a wide range of noise densities, ranging from 10 % to 70 %.

In [11], an impulse noise removal algorithm based on decision making and signal adaptive median filtering was proposed. the algorithm can be used to detect noise accurately while maintaining high SNR values – without smearing fine details and edges of the image. This idea of homogeneity level was introduced for the pixel values considering their global and local statistical characteristics. Correlation among the adjacent pixels was represented by the cooccurrence matrix technique and the upper and lower limit of the homogeneity level is derived from the cooccurrence matrix. There are two stages to noise detection: noise candidates are initially selected with the homogeneity level; a subsequent refinement process was then used to remove false detections. The noise detection scheme was not based on a quantitative decision measure but rather was based on qualitative structural information, and was not hampered by tedious computations for optimization of the threshold values. The experimental results showed that the scheme was much better than other median filters, in terms of suppressing noises and preserving details. A novel algorithm based on decision was proposed in [12] for image restoration in the case of highly corrupted images by impulse noise. The algorithm demonstrated much higher image quality than a Standard Median Filter (SMF), Adaptive Median Filters (AMF), a Threshold Decomposition Filter (TDF), cascade and recursive nonlinear filters. Unlike other nonlinear filters, the proposed method only eliminated corrupted pixel based on median value or the neighboring pixel value. Based on this, the proposed method successfully eliminated the noise even at a high noise level of 90 % and preserved the edges at a high as 80 % noise level. The test of the proposed algorithm is performed on various images and the results obtained were satisfactory both qualitatively and quantitatively in terms of the image.

In [13], the authors presented a novel approach for the removal of salt and pepper noise, namely, based on Pixel Density Filter (BPDF). The first step of the method was to decide whether or not a pixel is noisy, and then decided adaptively the window size that accepts the noisy pixel as the window center. The maximum frequency of the entity with the same value in the window is selected and used as the value of the corresponding pixel. By using 18 test images, the results of Peak Signal-To-Noise Ratio (PSNR), Structural Similarity (SSIM), Image Enhancement Factor (IEF), Standard Median Filter (SMF), Adaptive Median Filter (AMF), Adaptive Fuzzy Filter (AFM), Progressive Switching Median Filter (PSMF), Decision-Based Algorithm (DBA), Modified Decision-Based Unsymmetrical Trimmed Median Filter (MDBUTMF), Noise Adaptive Fuzzy Switching Median Filter (NAFSM), and BPDF. It is shown that the BPDF method performs better than the above methods, in the low and medium noise density range. In order to eliminate Salt And Pepper (SAP) noise at all densities, in [6] they presented a technique called Different Applied Median Filter (DAMF). Next, they discussed some of its fundamental concepts. then used Peak Signal to Noise Ratio (PSNR) and Structural Similarity (SSIM) for a few photos, including Cameraman and Lena, to compare the outcomes of the DAMF method with a few other approaches. For instance, the PSNR and SSIM results of the PSMF, DBA, MDBUTMF, and NAFSM techniques for a Cameraman image with an SAP noise ratio of 30 % are 28.27/29.28/29.44/32.09 and 0.9044/0.9324/ 0.7740/0.9494, respectively, but the PSNR and SSIM results of the DAMF method are 36.83 and 0.9844, respectively. Finally, they demonstrated that DAMF could effectively eliminate SAP noise across all densities.

The authors in [15] suggested using an Adaptive Frequency Median Filter (AFMF) to eliminate the noise caused by salt and pepper. The adaptive condition of the Adaptive Median Filter (AMF) is also used by AFMF. Instead of using the AMF median, AFMF uses the frequency median to restore the grey values of the corrupted pixels. The frequency median emphasizes the uniqueness of grey values and can filter out noisy pixels when assessing a grey value of the window's center pixel. As a result, the frequency median yields a grey value that is more similar to the initial grey value than the AMF median. AFMF hence

performs better than AMF. The authors conducted experiments using the TESTIMAGES data set and a range of natural photographs from the MATLAB library. They also contrasted the denoising outcomes of AFMF with those of other cutting-edge denoising techniques. The outcomes demonstrated that AFMF denoises more successfully than alternative techniques. In [16] they proposed a modified decision-based unsymmetrical trimmed median filter algorithm for the restoration of color and grayscale images severely distorted by salt and pepper noise. When other pixel values, 0s, and 255s are present in the chosen window, the suggested approach replaces the noisy pixel with the trimmed median value; when all of the pixel values are 0s and 255s, the noise pixel is replaced with the mean value of all the elements in the chosen window. The suggested approach outperformed the Progressive Switched Median Filter (PSMF), Standard Median Filter (MF), Decision Based approach (DBA), and Modified Decision Based Algorithm (MDBA).

To address the problem of salt-and-pepper noise in digital images, [17] introduced a Nonlocal Adaptive Mean Filter (NAMF) in literature. Their approach is based on the adaptive window detector and nonlocal mean filtering strategy. This adaptive detector first detects the corrupted pixels by dynamically determining the neighborhood size based on local image properties and then a nonlocal adaptive mean filter is used to estimate the intensity of pixels with noise by referring to similar image regions. A number of experiments showed that NAMF yielded superior restoration results compared to several of the common impulse-noise removal techniques for a broad range of noise densities and retained the edges and fine structures in the image. It demonstrates the increasing interest in using adaptive noise detection as well as nonlocal image statistics for denoising. In [18] they proposed an algorithm for the salt and pepper noise removal, which introduces detail-aware noise removal to overcome the drawback of texture loss while using median-type filters for salt and pepper noise removal. They start by using median-type filter to remove the impulse noise, and then use an adaptive nonlocal bilateral filter to minimize the restoration error caused by the first filter. The authors showed that the adaptive bilateral filtering method combined with median based restoration method significantly enhances the preservation of edges and recovery of texture to improve the effectiveness of the noise suppression property, by statistically analyzing the residual errors. They emphasize the need for a combination of filtering methods to be implemented rather than just median filtering.

The authors in [19] discussed the theoretical behavior of adaptive morphological filters in the suppression of salt-and-pepper noise. Unlike only median statistics, the proposed framework is based on adaptive mathematical morphology, which helps to preserve the boundary of the objects while removing impulse noise. Under various contaminations, the authors studied the filtering behavior and showed that the adaptive morphological processing has better edge preservation than conventional nonlinear filters. Their study helps to understand how adaptive neighborhood operations could be deployed to achieve reduction of impulse noise while retaining the structural image information. One of the most crucial steps in digital image processing for restoring an image's structural integrity and visual quality is denoising. Conventional techniques frequently have drawbacks such as over-smoothing, processing complexity, and the inability to maintain important features, especially edges. To overcome these difficulties, [20] presents a hybrid denoising technique that combines Adaptive Median Filter (AMF) and Modified Decision-Based Median Filter (MDBMF). The MDBMF significantly reduces noise while maintaining edges by selectively recovering damaged pixels without impacting intact regions, whereas the AMF dynamically modifies window sizes to accurately detect noisy pixels. The objective assessments that support the subjective analysis demonstrate that the hybrid approach's performance far surpasses that of current state-of-the-art techniques. Nine benchmark photos from a standard and medical dataset—specifically, images of the liver and chest with varying noise densities ranging from 10 to 90 %—are used for the test. The hybrid technique outperforms the state-of-the-art approaches in terms of performance, as demonstrated by quantitative evaluations of PSNR, MSE, IEF, SSIM, FOM, and VIF. Compared to other techniques like BPDF, AT2FF, and SVMMF, the PSNR improved by up to 2.34 dB, the IEF improved by more than 20 %, and the MSE improved by up to 15 %. Improved structural similarity is confirmed by improvements in SSIM values of up to 0.07. Additionally, the hybrid approach's outstanding performance is demonstrated by the FOM and VIF measures, which both surpassed all other denoising algorithms assessed, reaching 0.68 and 0.61, respectively. To remove salt-and-pepper noise while preserving the significant image boundaries, [21] presented an edge-adaptive total variation model. It uses edge detection and median filtering in homogeneous regions, and adaptive total variation model in edge regions to separate the edge regions from the non-edge regions. The method effectively attenuates impulse noise while preserving sufficient edge details of the image, thanks to the use of these two restoration techniques. The experimental results well justified the advantages of combining adaptive variational model with classical median filter based denoising method in terms of edge preservation capability.

In order to eliminate high-density salt and pepper noise, [22] introduced Nearest Value Based Mean Filter (NVBMF) which is a two-stage adaptive filtering algorithm. In the first step, the intensity of each noisy pixel is substituted by the intensity of the closer intensity in its neighboring pixels or by the average of the equally close intensity if there are more than one. The restored image is further enhanced in the second stage by an adaptive mean filtering operation based on the estimated noise density. For the

evaluation, the proposed method was applied to a number of benchmark image datasets, and compared with many state-of-the-art impulse-noise removal methods such as the Adaptive Frequency Median Filter (AFMF), Adaptive Weight Mean Filter (AWMF), Adaptive Switch Weight Mean Filter (ASWMF), and several Riesz- and Cesàro-based filters. The results of the experiments showed that NVBMF provided competitive and, in certain cases, even better PSNR, SSIM and Image Enhancement Factor (IEF), especially under high noise density conditions which revealed a capable performance in preserving information content of the image while reducing the impulse noise. In [23] presented an optimization-based adaptive switching filter using Modified Decision Based Unsymmetric Trimmed Median Filter (MDBUTMF) along with an optimization technique Hybrid Bee Colony Optimization-Firefly Bat Intelligence Algorithm (Hyb-BCO-FBIA). The optimization program adapts the filtering parameters in an automatic manner for better restoration quality in the case of a strong salt-and-pepper noise contamination. Experimental comparisons revealed that the proposed optimization framework outperform two or more several conventional techniques of adaptive median filtering in terms of PSNR and MSE at the same time maintaining the edges of images more effectively. In this work the authors illustrate the ever-growing trend of using intelligent optimization techniques to improve traditional impulse-noise removal algorithms. [24] outlined a two-stage filtering scheme consisting of an impulse-noise detector based on the characteristics differences and an adaptive mean filter based on the direction filter. The identification of noisy pixels is performed in both stages: In the first stage gray-level extrema and local characteristic differences are used to identify noisy pixels; and in the second stage, only pixels identified as noisy are restored using directional averaging. It was found through experiments that the proposed detector was effective in reducing the false classifications of noise-free pixels and enhanced the edge preservation from conventional median based detectors, especially at high density of impulses. This work confirms that dividing noise detection from pixel restoration is an effective approach which is followed by many contemporary adaptive algorithms for the extraction of noise from images.

Based on these observations, a Simplified Enhanced Median Filter (SEmF) is introduced in this article to suppress the salt-and-pepper noise in grayscale and color images. The proposed method differs from the traditional median and average filters that process all pixels without distinction, by only taking care of the possible noisy pixels whose intensities are related to the extreme gray levels of impulse noise. The pixels which are not changed during the filtering process are noise free, thus eliminating the need for unnecessary changes to the image information. Furthermore, the proposed algorithm uses an adaptive multi-window approach that uses a selectable padding factor to enable the use of larger neighborhoods as noise density increases so that more contextual information is necessary to ensure the correct median estimation. This design makes it possible to keep the proposed filter having enough restoration performance in a large range of impulse-noise levels, while more effectively preserving image details than is provided by conventional filter designs.

This work makes the following major contributions. A simplified selective median filtering framework is first introduced, which is applied to only some noisy pixels in the image and leaves all of the other pixels unchanged. Second, an adaptive multi-window median estimation strategy is introduced to enhance the restoration result under low and high intensity salt-and-pepper noise. Thirdly, the proposed algorithm works for both grayscale & color images without any modifications to the structure, as it degrades color channels separately. Finally, experimental results have been compared by the Mean Squared Error (MSE) and Peak Signal-to-Noise Ratio (PSNR) and filtering time in order to prove the effectiveness of the proposed method when compared with the conventional median and average filtering methods.

2. Methodology

Recently, various digital filters are used to remove SPN [1-5], a lot of these filters are based on standard Median Filter (SMF) And Standard Average Filter (SAF) A median based filtering technique has been one of the most successful techniques for fixed valued impulse noise filtering, as the median value is not as susceptible to extreme value outlier noise. The main drawback of the standard Median Filter (SMF) is that it performs the filtering process on all of the image pixels, both corrupted and uncorrupted ones. Many pixels that do not produce noise are thus replaced, losing the fine details of the image, making edges round off and degrading the texture of images, especially with repeated filtering or by using large filtering windows. The SMF and SAF have the following disadvantage [25-29]:

- SMF treats all pixels (clear pixels (CP) and possible noisy pixels (PNP), it uses a window and the pixel value will be replaced by the window median, while SAF also treats all pixels by using a window and replacing the pixel value with the average of this window. SMF and SAF will replace the image pixels even if the image is clear as shown in Fig. 1. it is shown in Fig. 1 SMF and SAV produced damaged images, while the presented filter kept the clear image without any changes;
- SMF and SAF filters do not differentiate between CPs and PNPs, and they are processed in the same manner, Fig. 2 shows how these filters deal with CPs and PNPs.

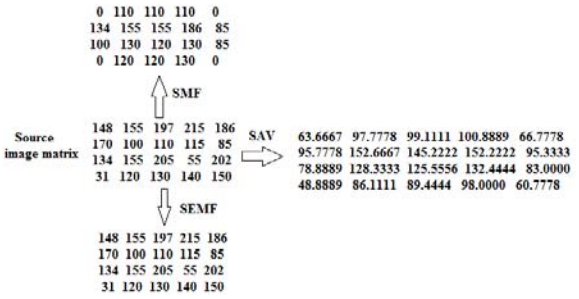


Fig. 1. Clear image filtering.

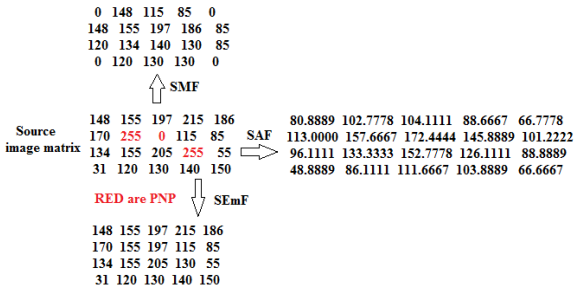


Fig. 2. Reducing SPN.

Proposed Simplified Enhanced Median Filter (SEmF) is based on the well-known selective processing philosophy, but with a simplified implementation. The pixels with gray level values at the extremes (0 or 255 in 8-bit images) are considered as potentially noisy pixels, while all the other pixels are treated as uncorrupted and hence are not modified. Because the detection strategy is based on pixel values being replaced by the minimum or maximum permissible gray levels, it is compatible with the statistical model of salt-and-pepper noise, and does not require unnecessary processing of the majority of pixels in the image. Limiting the restoration to noisy pixels that they consider "candidates" helps to avoid the loss of detail that is often found when the entire image is modified by the conventional median filter [9]. The proposed SEmF is different from the widely used median filter where a fixed neighborhood is applied throughout the image, and it introduces an adaptive multi-window restoration mechanism. The filtering process is user-controlled by the maximum neighborhood size (padding factor or PF). In this situation with relatively low impulse-noise density, a small neighborhood can be used, since most neighbouring pixels are not corrupted. However, under higher noise densities, a larger neighborhood will ensure that there will be enough valid pixels in the neighborhood to ensure that a good median estimate is calculated. Restoration has been demonstrated to be improved under severe impulse-noise contamination with similar adaptive window-expansion strategies that make it more likely to obtain representative neighborhood statistics [10].

The new multi-window strategy is a different implementation of classical adaptive median filters. In classical adaptive median filtering, the neighborhood size is increased until some prescribed statistical criteria are met, while in SEmF, the size of the neighborhood is evaluated in a predefined sequence of neighborhood size based on the padding factor. This design maintains the main benefit of adaptive neighborhood selection, and it is more easily implemented. Moreover, the maximum neighborhood size is given beforehand and thus the computational behavior of the proposed algorithm is known and can be tailored to the anticipated level of impulse noise and computational resources. Another special feature of the proposed algorithm is the retention of the image information. As only the noisy pixels are replaced, the original values of all the other pixels will be preserved. This is also important for maintaining edges and fine textures as these image structures are often lost by multiple corrections of already correct pixels. Many research works on switching and decision-based filters have shown that the visual quality and quantitative performance metrics like Mean Squared Error (MSE) and Peak Signal-to-Noise Ratio (PSNR) are improved significantly if some of the pixels are not replaced unnecessarily.

The replacement value in SEmF is calculated with the median of the neighborhood that has been selected if the computed median value is not in the minimal and maximal gray-levels. With this rule, one impulse value may not be replaced by another impulse value, which can happen if there is a lot of noise pollution in the local neighborhood. The same ideas have been used in adaptive and decision-based impulse-noise filters to achieve better restored accuracy in high noise density, by choosing replacement values from the "reliable neighborhood statistics" instead of "corrupted observations. The algorithm proposed is also directly available for both gray-level and color images. When processing color pictures, each color channel is treated separately, and the same selective filtering strategy is applied to each channel. Channel-wise processing is commonly used in image restoration based on median filtering, since it ensures the simplicity of the algorithm used for each individual image channel while also effectively minimizing impulse noise in each component image. The proposed filter design allows the filter to function without any changes to the detection and restoration methods.

The complexity of SEmF is mainly determined by the padding factor and the neighborhood sizes used in the computation, from a computational point of view. If the impulse-noise density is low, the smallest neighborhood is enough, and the computational complexity is similar to that of conventional median filtering. Additional neighborhood evaluations provide more computational cost under higher noise densities, but yield better probability of obtaining a reliable median estimate which in turn results in better restoration quality. Furthermore, if the image is noise-free in some regions, many of the neighborhood evaluations will not be computed since only the candidate noisy pixels are evaluated, which reduces the processing time compared to algorithms that

process all pixels. This selective computation is an attractive compromise in terms of denoising and computational efficiency.

The presented SEmF will use the following input matrices:

- Noisy input image (IM), this matrix is a 2D matrix [26-30], which requires processing and which contains the PNP, the number of these pixels will depend on the noise ratio;
- Padded matrix [31-35], this matrix can be obtained from IM by padding it using a padding factor (PF), this factor will determine the maximum window which can be used to treat the image pixels, (PF = 1: 3 by 3 window, PF = 2: 5 by 5 window, PF = 3: 7 by 7 window and so on). In the presented SEmF the maximum value PF was selected to be equal 5. This will give the filter the ability to use window with size 11 by 11 down to window with size 3 by 3, Fig. 3 shows an example of various padding of a given image;
- Binary image matrix (BIM): this image is a 2D image with size equal the padded IM size, and it will contain zeros and ones, zero means that the associated pixel is a PNP, while 1 means that the associated pixel is CP, Fig. 4 show the BIM obtained from the source noisy image matrix;
- Pixel window, this window is a 2D matrix; it will be used to replace the associated pixel with the median of this window. The presented SEmF will use various windows depending on the selected value of the PF, the maximum window size used here in this filter is 11 by 11 with PF equal 5. The median calculation can be repeated by repeating windows calculation starting from highest PF to lowest PF, Fig. 5 shows some possible used pixel windows.

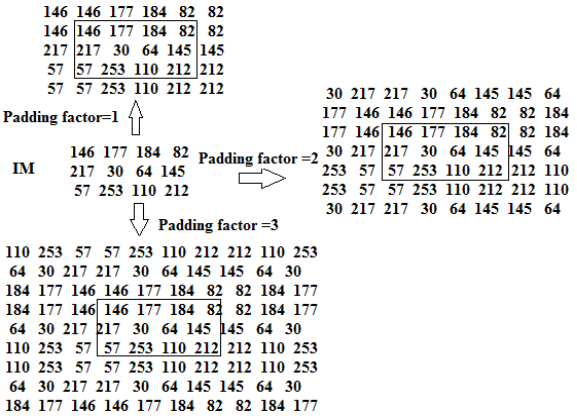


Fig. 3. Image matrix padding example.

The filter version can be selected by using the value of the selected padding factor (PF), version 1 will be selected when PF equal one, while the second version will be selected when PF is greater than 1. Version 1 will be used to remove SPN with low ratio, while version 2 will be used to remove SPN with higher noise ratio. The number of used windows to calculate the median value, which will be used to replace the value of PNP depends on the selected value of PF, Table 1 shows possible values of the PF and the associated windows to be used:

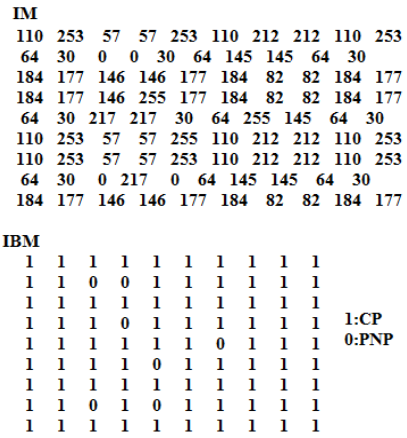


Fig. 4. Binary image matrix (BIM) example.

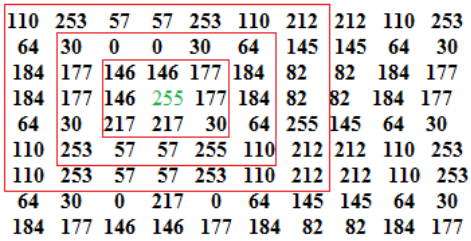


Fig. 5. Possible used pixel windows.

The presented SEmF will be implemented using one of the following algorithms:

- One window calculation algorithm (SEmF_1w);
- Multiple windows calculation algorithm (SEmF_mw).

Table 1. PF and the used windows.

PF	Algorithm version	Highest window	Used windows to calculate the median
1	SEmF_1w	W1 = 3 by 3	W1
2	SEmF_mw	W2 = 5 by 5	W2 down to W1
3	SEmF_mw	W3 = 7 by 7	W3 down to W1
4	SEmF_mw	W4 = 9 by 9	W4 down to W1
5	SEmF_mw	W5 = 11 by 11	W5 down to W1

Increasing the number of used windows will increase the time required to remove the SPN. The presented filter versions can be combined in one algorithm, and the selected value of the PF will determine the used version. The presented filter will be able to remove the noise from gray images, if the noisy image is a color one, then each 2D color-channel matrix must be treated separately.

SEmF Algorithm

Input: Noisy image a1, padding factor PF.
Output: Denoised image x.
Read a1.
Initialize PK
If the image is color call the filter 3 times, one time for each color 2D matrix.
Presented filter:
For each PF starting from the highest value down to 1 do:
Pad the image matrix.
Calculate the BIM.
For each pixel do
If the pixel is a CP then move to the next pixel.
Apply windows calculation:
For each window replace the PNP with the window median if the window median is greater than zero and less than 255.

Fig. 6 illustrates a MATLAB function, which can be used to implement the presented filter. The presented SEmF method is designed for the salt and pepper impulse noise model, in that, the corrupted pixels are commonly represented by the extreme intensity values of 0 and 255. Therefore, the proposed method identifies pixels with intensity values either 0 or 255 as corrupted pixels. However, pixels with values other than 0 or 255 assumed to be uncorrupted and are preserved.

This detection strategy provides a simple and computationally efficient technique for identifying the impulse noise pixels. Nevertheless, it depends on the assumption that the pixels with extreme values in the observed image are an impulse noise process generation. Indeed, in natural images, intensity values of 0 and 255 may also occur legitimately, as in dark region, saturated areas, strong image boundaries and dark regions. Based on that, such pixels may potentially be classified as corrupted and modified by SEmF. Based on that, the applicability of the current SEmF is primarily considered within the assumed salt and pepper impulse noise model. The possibility of false detection of naturally occurring 0- and 255-valued pixels is recognized as a limitation of the proposed approach.

```
function X=ZQF(A,PF)
%A: input noisy image; PF:padding factor
%X: Denoised image
A=double(A);
 %%For each PF staring from highest to lowest:
for p=PF: 1:1
%%image padding
 pA=padarray(A,[p p],'symmetric');
%%calculating BIM
 pB=(pA.~=0 & pA.~=255);
 %%get the image size
[m,n]=size(pB);
%%for each pixel do
 for i=1+p:m-p
  for j=1+p:n-p
%%if the pixel is PNP   (condition 1)
    if (pB(i,j)==0)
%%Apply windows calculations for the pixel
      for k=1:p
%%the window median must be greater than 0 and less than 255 to apply PNP replacement  (condition 2)
        if ((0<median(median(pA(i-k:i+k,j-k:j+k)))) & (median(median(pA(i-k:i+k,j-k:j+k)))<255) & (pA(i,j)==0| pA(i,j)==255))
          %%get the window
           Wk=pA(i-k:i+k,j-k:j+k);
          %%find the window median and replace the PNP with the median
           A(i-p,j-p)=median(median(Wk));
        break;
        end
      end
    end
  end
 end
end
 X=uint8(A);
end
```

Fig. 6. Presented filter MATLAB function.

The SEmF algorithm operates according to the following sequence:

1. Input and initialization: The padding factor (PF) and the noisy image α1 are given as an input. The filtering procedure is applied independently to the color image to each of the three color channels;
2. PF processing order: In this step, the padding factor is processed from the highest value down to PF = 1. Based on this, the filtering procedure starts with the largest predefined processing configuration and subsequently proceeds toward the smaller configurations;
3. Padding: For each PF, the image matrix is padded according to the padding factor required to construct the corresponding processing windows. The padding operation is performed before the BIM and window calculations for the PF;
4. BIM calculation: For each PF, the Binary Image Matrix (BIM) is calculated from the image being processed. This value used to identify the pixels corrupted or uncorrupted;
5. Pixel by pixel processing: The image is then scanned pixel by pixel. If the current pixel is identified as a clean pixel by the BIM, it is preserved and the algorithm move on to the next pixel directly;
6. Processing of noisy pixels: If the pixel is identified as a potential noisy pixel, the predefined processing windows are evaluated sequentially. For each window, the median value of the valid pixels within that window is calculated;
7. Replacement criterion: A PNP is replaced by the calculated window median only when the median satisfies;
8. 0 < median < 255;
9. Completing process.

3. Results and Discussion

3.1. Results

The performance of the presented SEmF will be evaluated using the following parameters:

- The quality of the denoised image Y reference to a clear image X, this quality can be measured by calculating the mean square error (MSE) (see equation 1) between the two images, and the peak signal to noise ratio (PSNR) (see equation 2) calculated between the two images, the lower MSE and the higher PSNR point to a denoised image with good quality.

$$\mathrm{MSE}(X,Y) := \frac{1}{mn}\sum_{i=1}^{m}\sum_{j=1}^{n}\left(x_{ij}-y_{ij}\right)^2, \tag{1}$$

$$\mathrm{PSNR}(X,Y) := 10\log\left(\frac{255^2}{\mathrm{MSE}(X,Y)}\right) \tag{2}$$

- Filtering time (FT) in seconds.

A color image (lena.png) was affected with SPN with low ratio (NR is low when NR is less or equal 5 %), the PF was varied, the MSE, PSNR and FT were calculated and Table 2 shows the obtained results:

Table 2. Performance of the presented SEmF when varying PF using a low ratio noise (NR = 1 %).

PF	MSE	PSNR	FT
1	1.1192	**47.6349**	0.4840
2	1.1030	**47.6983**	0.7570
3	1.2303	**47.2355**	1.2620
4	1.2444	**47.1860**	1.3820
5	1.2553	**47.1481**	2.0230

From Table 2 it is shown that selecting PF with 1 will give the best performance, so for low SPN ratio it is recommended to use the first version of the presented filter (using only one window).

The previous experiment was repeated by using a noisy image with SPN ratio = 50 %, and table 3 shows the obtained performance parameters results:

Table 3. Performance of the presented SEmF when varying PF using a high ratio noise (NR = 50 %).

PF	MSE	PSNR	FT
1	1940.4	**15.2536**	6.7800
2	136.3988	**26.7824**	8.6500
3	108.5730	**27.7743**	8.7440
4	105.9412	**27.8810**	9.0070
5	107.3995	**27.8217**	9.3710

From Table 3, it can be observed that PF = 4 provides the best overall performance under the high salt-and-pepper noise condition (NR = 50 %). PF = 4 achieves the lowest MSE (105.9412), the highest PSNR (27.8810 dB), and a shorter filtering time (9.0070) compared with PF = 5, which has an MSE of 107.3995, a PSNR of 27.8217 dB, and a filtering time of 9.3710. Therefore, PF = 4 is selected as the optimal configuration for the high-noise condition considered in Table2.

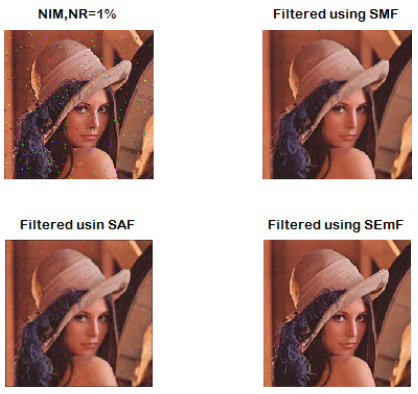


Fig. 7. Filtering NIM with low NR (NR = 1 %).



Fig. 8. Filtering NIM with high NR (NR = 30 %).

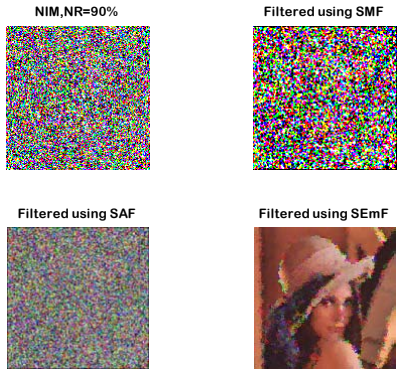


Fig. 9. Filtering NIM with high NR (NR = 90 %).

The image “lena.png” was affected by SPN noise using various NRs, the noisy image (NIM) was filtered using each of the filters: SMF, SAV and the presented SEmF, the quality parameters of the denoised images were calculated and Table 4 shows the obtained results.

Table 4. Quality results.

NR (%)	SAF		SMV		SEmF	
	MSE	PSNR	MSE	PSNR	MSE	PSNR
1 (low)	105.3041	**27.9072**	39.6728	**32.1467**	1.1561	**47.4936**
2 (low)	129.6134	**27.0019**	40.9721	**32.0067**	2.0895	**44.9285**
3 (low)	152.0068	**26.3128**	42.1428	**31.8830**	3.2743	**42.9818**
4 (low)	184.8466	**25.4618**	45.3452	**31.5654**	5.2566	**40.9245**
5 (low)	203.3728	**25.0469**	46.1149	**31.4924**	6.0648	**40.3038**
10 (high)	348.4787	**22.7076**	60.6322	**30.3042**	11.3460	**37.5816**
20 (high)	673.4300	**19.8492**	132.5255	**26.9083**	25.5604	**34.0567**
30 (high)	1057.1	**17.8899**	356.3827	**22.6101**	46.2195	**31.4836**
40 (high)	1521.3	**16.3085**	973.4563	**18.2473**	70.2549	**29.6635**
50 (high)	2066.4	**14.9787**	2124.6	**14.8588**	111.3595	**27.6625**
60 (high)	2673.8	**13.8604**	4226.8	**11.8692**	159.5115	**26.1017**
70 (high)	3343.6	**12.8897**	7148.2	**9.5882**	228.1709	**24.5473**
80 (high)	4099.5	**12.0001**	11051	**7.6966**	331.3728	**22.9299**
90 (high)	4803.9	**11.3152**	15239	**6.3010**	487.4655	**21.2533**

From Table 4 it is shown that the presented SEmF enhanced the quality of the denoised image when this image is affected with SPN with low or high NRs, SEmF gave better results for the values of MSE and PSNR as shown in Fig. 10.

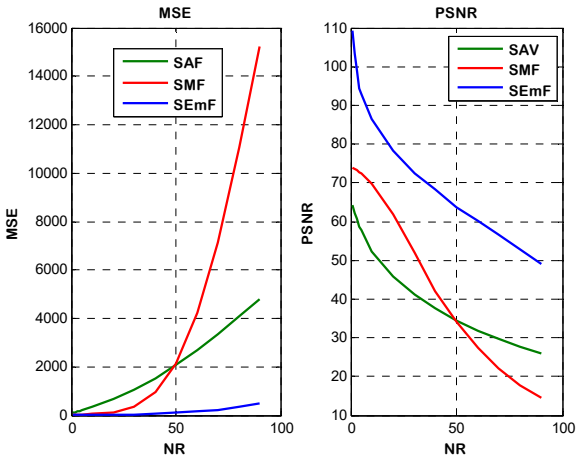


Fig. 10. Quality parameters comparisons.

3.2. Discussion

The experimental results show that the proposed Simplified Enhanced Median Filter (SEmF) can always restore better quality than the Standard Median Filter (SMF) and the Standard Average Filter (SAF) for both low- and high-density salt and pepper noise. The quantitative evaluations of Mean Squared Error (MSE), Peak Signal-to-Noise Ratio (PSNR) and filtering time (FT) are widely used in image denoising algorithms and were used to assess the performance. In the first experiment, the effect of the padding factor (PF) on restoration performance was studied. The results show that when the ratio of noise to impulse (NR = 1 %) is low, the single-window version of SEmF (PF = 1) yields the minimum MSE, maximum PSNR and the fastest execution time for the images corrupted with low NR value. This is in line to the properties of low density impulse noise, which has the following properties: Most of the neighboring pixels are uncorrupted and only a small local neighborhood is enough to estimate the median value reliably. Under these conditions, increasing the size of the window adds needless calculations but does not boost restoration accuracy. The same conclusion can be drawn for adaptive median filtering, in which the use of larger neighborhoods is beneficial only if there is a large number of corrupted pixels in the neighborhood.

A different behavior is observed for heavily corrupted images. The results of the experiments demonstrate that the quality of the restoration is significantly enhanced with the multi-window implementation when the impulse-noise ratio becomes 50 %, because the MSE is much lower and the PSNR is much higher compared with the single-window implementation. The larger neighborhood makes it more likely that there will be enough uncontaminated (or uncorrupted) pixels in it to obtain a more representative median value, which will help to restore heavily contaminated areas. In high noise conditions the gain in restoration quality is greater than the time it takes to filter with larger window sizes. This relationship between the computational complexity and the accuracy of the restoration has also been noted in the adaptive and switching median filters reported in the literature. The proposed selective restoration strategy is further highlighted by the comparison with SMF and SAF. The SAF takes linear averaging in the local neighborhood and the conventional SMF replaces all image pixels, including corrupted ones. Both methods, therefore, change an excessive number of correct pixels, resulting in blurring of the edges and loss of fine image details. SEmF restores only the pixels that are detected as INC (impulse-noise candidates) and leaves the other pixels unchanged. This selective processing greatly minimizes the unwanted changes of valid image data and helps to improve PSNR and decrease MSE as seen in the results. This behavior is in keeping with the design philosophy of decision based and switching filters, whose performance it has consistently surpassed by decoupling the noise detection and restoration processes, as is conventional median filtering. It is worth noting that these results were obtained using MATLAB R2024b, using machine with (CPU model, RAM, GPU if applicable, e.g., Intel i7-8650U, 24 GB RAM, RTX 3060Ti 12 GB), image data characteristics 20×200×1, unit 8, it takes as an average overall running time running time 50 ms.

Table 4 shows that SEmF achieves lower MSEs and higher PSNRs than the other two cases (SMF and SAF) over all the noise densities studied. The performance appears to be more noticeable as the impulse-noise density becomes stronger, suggesting the proposed adaptive multi-window approach is more effective under severe degradation. The visual comparisons shown in Fig. 7-10 are also in line with the quantitative analysis results, as they demonstrate the improved preservation of edges, image structures and fine details following filtering with SEmF in comparison to the conventional methods. The other thing to note is computational efficiency. The multi-window implementation is more complex in the case of higher padding factors, but by not applying restoration techniques to pixels already classified as uncorrupted, the algorithm is able to avoid unnecessary computations. This means that the number of computations is significantly less than it would be if each of the image's pixels were processed many times with different neighborhood sizes. The proposed algorithm is an effective compromise between the quality of image restoration and the time taken to execute the algorithm and is thus suitable for practical applications of image processing, where the accuracy and execution time are important. It is worth noting that the limitation of the proposed SEmF is its reliance on the identification of 0 and 255 valued pixels as candidate impulse-corrupted pixels. Even this assumption is good for the salt pepper noise models used in the given experiments, however, natural values of image pixels may also have these extreme intensity values. As a result, a genuine saturated white or black pixel may be incorrectly classified as noisy and then modified. This limitation is more significant in images containing bright

regions, high contrast structures, saturated areas or large dark areas. Consequently, the current structure does not explicitly distinguish between a naturally occurring extreme valued pixels and the corrupted ones.

Recent WMF [35] and MWMF methods [36] share some concepts with SEmF, especially selective processing, padding operation and neighborhood-based filtering. These common concepts are therefore not claimed as individual novel contributions of SEmF. Instead, the novelty of SEmF lies in the specific combination and sequence of its processing steps. However, the novelty of SEmF lies in the specific combination and sequence of its processing steps.

In summary, the experimental results demonstrate that the proposed SEmF can efficiently achieve a selective noisy-pixel detection, as well as an adaptive median estimation. The algorithm avoids discarding unchanged pixels, reduces the loss of details and has better restoration performance than the traditional median and average filters, especially in the presence of moderate and high salt-and-pepper noise. The results are in line with previous research that demonstrated that selective switching strategies and adaptive neighborhood processing methods can offer substantial benefits when compared to indiscriminate filtering.

4. Conclusion

A simple and efficient SEmF was presented, the used filter was simple and easy to implement, and it can be efficiently used to remove salt and pepper noises with low and high noise ratios. The presented method was capable of denoising grayscale and color images, changing the image did not require any changes in the presented filter algorithm. The presented filter can be implemented in two versions: the first version used one window to calculate the median and it was recommended to be used to eliminate salt and pepper noise with low noise ratio, while the second version used multiple windows to calculate the median and it was recommended to be used to eliminate salt and pepper noise with high noise ratio. The presented filter processed only the possible noisy pixels keeping the clear pixels without changing. The possible noisy pixels were filtered base on the pixel value and the calculated window median, this pixel was replaced when the pixel value was equal 0 or 255 and the calculated window median was greater than 0 and less than 255.The presented SEmF enhance the performance of standard median and standard average filters by improving the quality of the denoised images, this filter optimized the values of MSE and PSNR for the denoised image. Future work will investigate contextual and neighborhood-based decision criteria that can distinguish genuine extreme valued image structure from impulse corrupted pixels, thereby reducing the possibility of false detection while preserving important image details.

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