

Direction Based Efficient Weighted SMF for High Density Salt and Pepper Noise Removal

¹A.Queen, ²G.Shree Bindhiya Devi, ³N.Rubala, ⁴Thusnavis Sandhiya

UG Student, Department of ECE, Rajas Engineering College, Vadakkangulam, India

UG Student, Department of ECE, Rajas Engineering College, Vadakkangulam, India

UG Student, Department of ECE, Rajas Engineering College, Vadakkangulam, India

UG Student, Department of ECE, Rajas Engineering College, Vadakkangulam, India

ABSTRACT: A direction based weighted switching median filter for restoration of images corrupted by high density impulse noise is proposed. The Switching Median filters(SMF) are selectively applied such that only noisy pixels undergo the filtering operation. This uses a detection mechanism to reliably identify candidate noisy pixels in the image. The direction weighted median filter is then combined with switching median filter to get a direction weighted switching median filter by suppressing impulse noise while preserving image details using uncorrupted pixels in the selected four possible directions in order to replace noise corrupted pixel with estimated noise free weighted median value. It is suitable for real time implementation and application. Experimental evaluation shows in producing better denoising and preservation of fine details for highly corrupted images than the SMF algorithm.

KEYWORDS: Impulse noise, median filter, noise detection, SMF, weighted switching median filters, denoising.

1. INTRODUCTION

CHANNEL transmission errors and faulty switching of acquisition devices may result in corrupting images with impulse noise. Pixels contaminated with impulse noise are characterized by having relatively low or high intensity values when compared to their neighboring pixels. This could dramatically affect images quality and possibly make them unsuitable for human or machine vision applications. In attempt to restore the original values of noisy pixels, filtering techniques are usually applied with the objective of suppressing the noise while minimizing the distortion introduced to the sharpness of edges and details in the original image. Various filtering methods have been suggested for the removal of impulses from the digital images.

Most of these methods are based on median filtering techniques, which use the rank order information of the pixels in the filtering window. The standard median filter [1] removes the noisy pixels by replacing test pixel with the median value of the pixels in the window. This technique provides a standard noise removal performance but also removes thin lines and dots, distorts edges and blurs image fine textures even at low noise ratios. The weighted median filter [2], center weighted median filter [3] and adaptive center weighted median filter [4] are modified median filters. They give extra weight to some pixels of the filtering window and thus these filters achieve betterment to the standard median filter. The standard and weighted median filters are incapable of making distinction between the noisy and noise less pixels of the noisy image. Hence these filters distort the noise free pixels of the image. For such problems, switching median filter [5] has been proposed in which an impulse detector has been introduced to classify the center pixel of the test window. If the center pixel is detected as noisy then that pixel is replaced by standard median value of the test window.

As a result, many impulse detection methods along with switching median filters have been proposed [4] - [8]. Among them, an iterative *pixel-wise modification of MAD* (median of the absolute deviations from the median) filter [8] is a robust estimator of the variance used to efficiently separate noisy pixels from the image details. The *tri-state median filter* [9] and *multistate median filter* [10] are improved switching median filters those are made using a

weighted median filter and an appropriate number of center weighted median filters. This is related to the fact that filtering in such algorithms is applied to all pixels in the image and ignoring the fact that not all pixels are noisy.

A bilateral filter [21] combined with an impulse detector that detects impulse noise according to the local image statistics was also proposed. In [22], noise detection incorporates edge directed approach to preserve the details and edges. A fuzzy technique that is capable of detecting and removing impulse noise was proposed in [23]. The technique relies on long range correlation within different parts of the image. The noise adaptive soft-switching median filter [24] applies an approach that utilizes the fuzzy-set concept to classify pixels into noise free pixels, isolated noisy pixels, non-isolated noisy pixels, and edge pixels. The direction based efficient weighted switching median filter for restoration of images corrupted by high density impulse noise is proposed. The switching median filter is the boundary discriminative noise detection (BDND) filter is proposed with enhanced improvements. The filtering process consists of two phases. The detection phase followed by a filtering phase. The first step is essentially a noise detection step which is based on clustering the pixels in the image in a localized window. After detecting noisy pixel positions in the image, filtering algorithm is applied to those detected pixels. This method employs a 5x5 window for noise detection and classifies the pixel into a “corrupted pixel” or “uncorrupted pixel” based on the boundaries calculated during the detection process. All uncorrupted pixels in the image are left unchanged by the filtering algorithm.

II. IMPULSE NOISE MODELS

Different image acquisition devices and transmission channels generate different kinds of noise, which may contaminate images. The type of noise considered in this paper is the impulse noise whose value is generally independent of the image signal.

The normal values of impulse noise is 0 or 255, Where as the noise value of random valued impulse noise can be of any number between 0 to 255,0 or 255.

Pixels are randomly corrupted by two fixed extreme values, 0 and 255, with the same probability.

For each image pixel at location (i, j) with intensity value $s_{i,j}$ the corresponding pixel of the noisy image will be $x_{i,j}$, in which the Probability Density Function of $x_{i,j}$ is,

$$f(x) = \begin{cases} p/2 & \text{for } x=0 \text{ white dot (salt)} \\ p/2 & \text{for } x=255 \text{ black dot (pepper)} \\ 1-p & \text{for } x=s_{i,j} \text{ noise-free pixels} \end{cases} \rightarrow (1)$$

Let $O_{i,j}$ and $X_{i,j}$ be the pixel values at location (i,j) of the original image and the noisy image, respectively, and $[n_{min}, n_{max}]$ be the dynamic range of the allowed pixel values. Then for an impulse noise model with noise probability (or noise ratio) ρ , we have

$$X_{ij} = \begin{cases} \xi_{ij} & , \text{ with probability } \rho \\ O_{ij} & , \text{ with probability } 1 - \rho \end{cases} \rightarrow (2.7)$$

where

$\xi_{i,j}$ is a noise value independent from $O_{i,j}$.

There are two cases of noise distributions for impulse noise:

- Fixed-Valued Impulse Noise
- Random-Valued Impulse Noise.

For fixed-valued (also called salt-and-pepper) impulse noise, the values of the corrupted pixels are equal to n_{min} or n_{max} with equal probability.

For random-valued impulse noise, however, the corrupted pixel values are uniformly distributed between n_{min} and n_{max} . For gray-level images with 8 bits per pixel (i.e., $n_{min}=0$ and $n_{max}=255$), the noise value $\xi_{i,j}$ of the first case corresponds to a fixed value of 0 or 255 with equal probability, while that of the second case corresponds to a random value uniformly distributed between 0 and 255.

Cleaning random-valued impulse noise is far more difficult than removing fixed-valued impulse noise because in the latter case, the differences of the pixel values between a noisy pixel and its noise-free neighbours are often significant.

III. SWITCHING MEDIAN FILTER

The Switching Median filters are selectively applied such that only noisy pixels undergo the filtering operation. This uses a detection mechanism to reliably identify candidate noisy pixels in the image. The filtering step relies on computing the median value of the uncorrupted pixels found in the window without any regard to the spatial relationship of these pixels to the noisy pixel, and the deviation of the pixels intensities from the median value.

The median value of uncorrupted pixels in the filtering window is calculated using

$$\text{median}\{W_{ij}\} = \text{median}\{x_{i-L,j-L}, \dots, x_{ij}, \dots, x_{i+L,j+L}\} \rightarrow (3)$$
 where

W_{ij} is the filtering window.

L is the length of window.

x_{ij} is the current image pixel.

The Switching median filter works based on a principle. First it tests to decide whether or not a given pixel is contaminated by impulse noise. A pixel is corrupted if the absolute difference between the median value in its neighbourhood and the value of the current pixel itself is greater than a given threshold. If corrupted, a classical median filter is applied, if not, the current pixel is noise free and will not be modified.

Consider an image corrupted by an impulse noise and the grey level value at position. Let be a square window surrounding this pixel. This window is of size $(2K+1) \times (2K+1)$, where K is an integer greater than zero. The output of the switching median filter is given by

$$Y(i, j) = \begin{cases} m(i, j), & \text{if } |m(i, j) - X(i, j)| > T \\ x(i, j), & \text{otherwise} \end{cases} \rightarrow (4)$$

where

$m(i, j)$ is the median value in the window W threshold is a fixed parameter.

The filtering process consists of two phases. The detection phase followed by a filtering phase. The first step is essentially a noise detection step which is based on clustering the pixels in the image in a localized window.

After detecting noisy pixel positions in the image, filtering algorithm is applied to those detected pixels. All uncorrupted pixels in the image are left unchanged by the filtering algorithm.

The limitation of switching median filter is that defining a robust decision measure is difficult because the decision is usually based on a predefined threshold value. In addition the noisy pixels are replaced by some median value in their vicinity without taking into account local features such as presence of edges.

Hence, edges and fine details are not recovered satisfactorily, especially when the noise level is high. In order to overcome these drawbacks direction based weighted switching median filter for restoration of images corrupted by high density impulse noise is proposed.

IV. PROPOSED METHODOLOGY

A direction based efficient weighted Switching Median Filter (SMF) for restoration of images corrupted by high density impulse noise is shown in Fig.1

The filtering process consists of two phases – detection phase followed by a filtering phase. The first step is essentially a noise detection step which is based on clustering the pixels in the image in a localized window.

After detecting noisy pixel positions in the image, filtering algorithm is applied to those detected pixels. All uncorrupted pixels in the image are left unchanged by the filtering algorithm. The filtering algorithm uses uncorrupted pixels in the selected four directions for taking a decision on the filtering window size. The filtering step relies on computing the weighted median value of the uncorrupted pixels found in the window without any regard to the spatial relationship of these pixels to the noisy pixel, and the deviation of the pixels intensities from the median value. Noisy pixels are replaced by a weighted median value of uncorrupted pixels in the filtering window or directional filtering window.

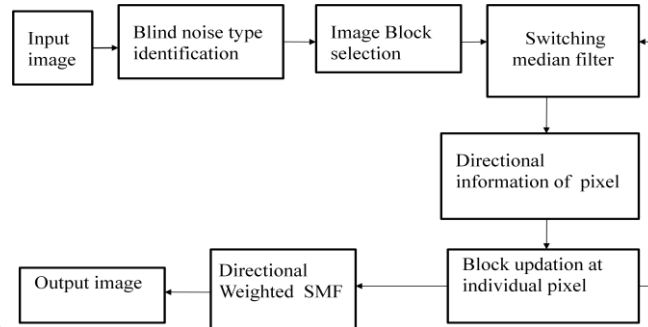


Fig.1 Block diagram for proposed method

The efficient direction based weighted Switching Median Filter substantially outperforms all existing median-based filters, in terms of suppressing impulse noise while preserving image details, suitable for real-time implementation and application. It reduce the impact of impulsive noise on the image and to design the system with fast computation. Thus yielding a very high noise detection accuracy, achieving zero miss-detection rate while maintaining a fairly low false-alarm rate, even up to 70% noise corruption.

A. Detection of Noisy pixels

An image containing salt-and-pepper noise will have darkpixels in bright regions and bright pixels in dark regions. Due toreason images that are impulse with salt and pepper noise appear aswhite and black dots.The amplitude of the Imposed noise in the image is very highas compared to the original signal strength of the image. Letintensity of the corrupted pixel in the range of two extreme values(minimum and maximum) in the range from 0 or Lposition (x, y) we find the value of CWhere Z denotes the Input image and values 1and 0represent noisy and noise free pixels.Here the noise level is detectedusing lookup table. Median filter is used for noise removal, which requires a median filter mask.

B. Weighted SMF

The operations involved in WMF are similar to SMF, except that WMF has weight associated with each of its filter element. These weights correspond to the number of sample duplications for the calculation of median value.

The filtered image $S=\{S(i,j)\}$ from WMF can be defined by the following equation

$$S(i, j) = \text{Median}(k, l) \in Wm, n\{Wm, n(k, l) \otimes D(i + k, j + l)\} \rightarrow (5)$$

Where operator \otimes indicates repetition operation.

C. Directional Weighted SMF

Directional weighted efficient switching median filter is also known as stick median filter, works by separating its 2-D filter into several 1-D filter components. Eachfilter component or stick, presented as a straight line, corresponds to a certain direction or angle θ . For a window of size $m \times n$ pixels, there are $m + n - 2$ sticks will be used. The computed median values from these 1-D filters are then combined to obtain the final result.

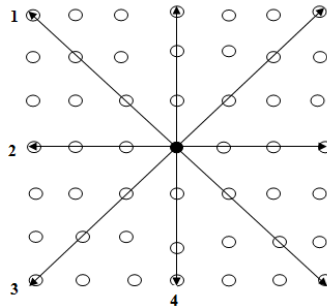


Fig.2 The four directions for impulse detection

The output intensity is defined as

$$S(i, j) = \max\{\text{Median}(k, l) \in W\theta\{D(i + k, j + l)\}\} \rightarrow (6)$$

where $W\theta$ is the stick.

Here, the output intensity is defined as the largest median value determined at each location.

D. Filtering Process

The filtering step relies on computing the median value of the uncorrupted pixels found in the window without any regard to the spatial relationship of these pixels to the noisy pixel, and the deviation of the pixels intensities from the median value. The filtering process consists of following steps.

1. Impose a 5x5 window, which is centered around the current pixel.
2. Sort the pixels in the window according to the ascending order and find the median, med, of the sorted vector .
3. Compute the intensity difference between each pair of adjacent pixels across the sorted vector and obtain the difference vector .
 - a) The Gradient is calculated at each image window block for edge and direction operation.
 - b) The filtering algorithm uses uncorrupted pixels in the selected four directions for taking a decision on the filtering window size.
 - c) The edges are classified as
 - Horizontal Edge
 - Vertical Edge
 - Omni directional Edge
4. For the pixel intensities between 0 and med in the ,find the maximum intensity difference in the of the same range and mark its corresponding pixel in the as the boundary .
5. Likewise, the boundary is identified for pixel intensities between med and 255; three clusters are, thus, formed.
6. If the pixel belongs to the middle cluster, it is classified as “uncorrupted” pixel, and the classification process stops; else, the second iteration will be invoked in the following.
7. Impose a 3x3 window, being centered around the concerned pixel and repeat Steps (2–5).
8. If the pixel under consideration belongs to the middle cluster, it is classified as “uncorrupted” pixel; otherwise, “corrupted. For the understanding of the algorithmic steps mentioned above, a 5 x 5 windowed sub image with the center pixel “202” is used as an example for illustrating the proposed BDND process as follows:

$$W = \begin{pmatrix} 255 & 255 & 47 & 255 & 39 \\ 50 & 255 & 255 & 0 & 0 \\ 0 & 0 & \mathbf{202} & 224 & 205 \\ 62 & 255 & 0 & 0 & 255 \\ 255 & 72 & 81 & 0 & 179 \end{pmatrix} \rightarrow (7)$$

V. EXPERIMENTAL RESULTS

Simulation results show that the proposed direction based weighted switching median filter performs better than many existing methods in both subjective and objective (PSNR) evaluations. In this section three examples are presented, which are: Lena, Boat, Peppers. Fig.3 shows the original test images and the noisy version of each that is corrupted by 80% impulse noise



Fig. 3 Experimental results for different images. (a) Original (c) SMF (d) Proposed approach.

Inspecting these results reveals the power of the two approaches in restoring the original images efficiently. However, careful investigation of the results proves the capability of the proposed approach in producing higher quality images when compared to the SMF algorithm. This is supported by the PSNR values that are shown in Fig. 4 under noise

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densities ranging from 10% to 70%. From these values, we can see how the performance of the two approaches is close to each other under low noise densities.

Peak-Signal-To-Noise Ratio

The phrase Peak Signal to Noise Ratio, often abbreviated PSNR, is an engineering term for the ratio between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation. Because many signals have a very wide dynamic range, PSNR is usually expressed in terms of the logarithmic decibel scale.



(c)(d)images. (b) Original images corrupted by 80% impulse noise.

The PSNR is most commonly used as a measure of quality of reconstruction of lossy compression codes. The signal in this case is the original data, and the noise is the error introduced by compression when comparing compression codes it is used as an approximation to human perception of reconstruction quality, therefore in some

cases one reconstruction may appear to be closer to the original than another, even though it has a lower PSNR is of higher quality.

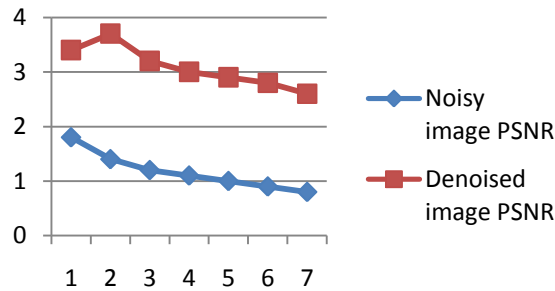


Fig.4 Comparison of PSNR values of lenasubimage

VI. CONCLUSION

The filtering algorithm uses uncorrupted pixels in the selected four directions for taking a decision on the filtering window size. The filtering step relies on computing the median value of the uncorrupted pixels found in the window without any regard to the spatial relationship of these pixels to the noisy pixel, and the deviation of the pixels intensities from the median value. Noisy pixels are replaced by a weighted median value of uncorrupted pixels in the filtering window or directional filtering window. The weight value assigned to each uncorrupted pixels depends on its closeness to the central corrupted pixel in the current filtering window. The direction based efficient weighted switching median filter substantially outperforms all existing median based filters, in terms of suppressing impulse noise while preserving image details, suitable for real time implementation and application. To reduce the impact of impulsive noise on the image upto 80% and to design the system with fast computation.

REFERENCES

- [1] S.E. Umbough, Computer Vision and Image Processing. Englewood Cliffs, Nj: Prentice- Hall, 1998.
- [2] O. Yli- Harja, J. Astola, and Y. Neuvo, "Analysis of the properties of median and weighted median filters using threshold logic and stack filter representation," IEEE transaction, Signal Processing, Vol.39, no. 2 PP. 395-410, Feb. 1991.
- [3] S. J. KO and Y. H Lee, "Center Weighted Median Filters and Their Applications to Image Enhancement," IEEE Transactions on Circuits and Systems, Vol. 38, No. 9, pp.984-993, Sep. 1991.
- [4] Tao Chen and Hong Ren Wu, "Adaptive Impulse Detection Using Center Weighted Median Filters", IEEE Signal Processing Letters, vol. 8, no. 1, pp. 1-3, January 2001.
- [5] T. Sun and Y. Neuvo, "Detail Preserving median based filters in image processing," Pattern Recognition Letter, vol. 15, no. 4, pp. 341-347, 1994.
- [6] S. Zhang and M. A. Karim, "A new impulse detector for switching median filters," IEEE Signal Processing Letters, vol. 9, no. 11, pp. 360-363, Nov. 2002.
- [7] G. Pok, Y. Liu, and A. S. Nair, "Selective removal of impulse noise based on homogeneity level information," IEEE Signal Processing Letters, vol. 12, no. 1, pp. 85-92, Jan. 2003.
- [8] Vladimir Crnojevic, Vojin Senk, Zeljin Trpovski, "Advanced impulse Detection based on Pixel- Wise MAD", IEEE Signal Processing Letters, vol. 11, no. 7, July 2004.
- [9] T. Chen, K.-K. Ma, and L.-h. Chen, "Tri- state median filter for image de noising," IEEE Transaction Image Processing., vol.8, no. 12, pp. 1834-1838, Dec. 1999.
- [10] Tao Chen and Hong Ren Wu, "Space variant Median Filters for the Restoration of Impulse noise corrupted images" IEEE Transactions on Circuits and Systems-II: Analog and Digital Signal Processing, Vol. 48, No. 8, pp. 784-789, August 2001.