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A COMPARATIVE STUDY OF MEDIAN BASED IMPULSE NOISE REDUCTION METHODS FOR COLOR IMAGES

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Abstract

With the explosion in the number of digital images taken every day, there is a growing demand for more precise and visually appealing images. Images captured by modern cameras, on the other hand, are eventually ruined by noise, which contributes to a reduction in visual image quality. Impulse noise is one of noise as white and black dispersed pixels that can be found in both gray and color images. The impulse noise model is comprised of Salt and Pepper (SAP) noise and random valued impulse noise (RVIN). So far, a lot of impulse denoising methods have been developed for the images (both gray and color). This article provides a comparative study of impulse noise reduction methods applied to color images wherein impulse noise reduction methods are studied with regard to their performance on color images and a thorough comparison is also carried out to cover all of the denoising methods in detail as well as the results they produce. These methods are contrasted with their functionality, relative performance and time complexity. Extensive simulations have been conducted on a set of standard images for performance evaluation of various denoising methods with regard to PSNR, SSIM and NMSE quality metrics.

Keywords:

Denoising, Filter, Image, Impulse Noise, Median Filter

1. INTRODUCTION

Noise is an unacceptable signal which can be triggered by various sources like low light, sluggish shutter, fill factor sensor, heat sensor, etc. There are different types of noise classified according to different considerations, as noise can have additive, phase, and multiplicative properties, and its model can be Gaussian, Poisson, Impulsive, Non-Gaussian, Rayleigh, Uniform, Speckle, Gamma, Exponential, Structured, Poisson-Gaussian, Quantization, Periodic, Brownian and White. Abrupt, unexpected and sharp fluctuations in an image signal may create white and black spots, i.e. impulse noise. To suppress or minimize impulse noise and recreate an original image approximation, many denoising filters or methods have been developed. After processing, it becomes very difficult to produce a correct reproduction of the original image due to factors like the complexity of the noise reduction or the imperfection of the denoising algorithm. In addition, there are certain instances where impulse reduction is not a major issue in extracting a bit of hidden information in a noise cluster, like in astronomical images. There are also some flaws in the median filtering technique used for a long time. It is not able to maintain the edges of the image processing and is comparatively costly with high time complexity. Different scholars and researchers made extensive attempts in the field of noise control and inhibition of impulses. Methods and techniques having a median filter basis are one such contribution to the elimination or removal of noise from impulses. All these methods have their own fortes and shortcomings in the quest of degrading images, thereby requiring more analysis to make them more improvised. There are a variety of uses like in camera adjustment, used in cases where a little delay, like in medical image processing, can be accepted. These cannot however be totally dismissed, since they are objective and for that reason still to be included.

Various median based filter variants are evaluated in this comparative study for noise removal in terms of their functionality, time complexity and relative performance. Filters are checked against color images and are highly used in different applications, like medical diagnosis by Magnetic Resonance Imaging (MRI), Computed Tomography (CT), Positron Emission Tomography (PET), Single Photon Emission Computerized Tomography (SPECT) etc. The comparison based on functionality explains the manner in which each particular filter is handled with noise, its relative progress, and anomalies, while time-complex analysis explores the algorithmic time needed for completion of the operation. An algorithm performance can be subjectively or objectively measured which in turn divided into two major categories: firstly, metrics like PSNR, MSE, MAE, VSNR, etc. whose quality prediction is solely dependent on statistical errors and the other metrics like SSIM, FSIM, VIF, ESSIM, etc. whose functionality is based on the Human Visual System (HVS).We evaluate the efficiency of all filters in both categories as they have different standards for the rating of image quality. The various quality judgment metrics used in this study are Peak Signal to Noise Ratio (PSNR), Normalized Mean Square Error (NMSE) and Structural Similarity Index Measure (SSIM).

The article is arranged as follows. The different filters that a number of researchers have applied to the noise suppression of impulses are compared based on their functionality in section 2. Section 3 is devoted to the comparative study of relative efficiency by utilizing different metrics for various filtering methods for noise suppression of impulses. Conclusion is drawn in the last segment.

2. COMPARISON USING FUNCTIONALITY

In this section, various median based filter variants for impulse noise reduction with regard to their functionality are discussed. We categorize these various variants of Standard Median Filter (SMF) based on the algorithmic logic, sense of accomplishment and flow mechanism into: a) Weighted Filters, b) Threshold Filters, c) Adaptive Filters, d) Switching Filters, e) Decision Filters, f) Hybrid Filters, g) Fuzzy Filters, h) Vector Filters and i) Deep Learning based Filters. A complete set of methods used, their pros and cons of all the variants are tabulated in Table.1. A diagrammatic representation of Median Filter Variants is given in Fig.1.

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Table.1. Median Filter Variants - Comparative Study

Title	Method (s) Used	Pros and Cons
SMF	Median	• Remove SAP noise • Treats all pixels equally • Fails to maintain edges
CWMF	Weighted Median	• Useful detail preserving smoothers • ACWA cannot suppress impulses
VMF	Maximum Likelihood Estimation	• Suppressing of Impulses • Preserving of edges
DWMF	Weighted Median	Preserve edges very well
FSMF	Switching Median	• Preserve image details and textures very well • Efficient with computation time
FRDM	Fuzzy Reasoning	• Simultaneously remove noise and preserve the detail • The edge's arbitrary directions cannot be preserved
NAFSM	Histogram, Fuzzy Reasoning	Efficient processing time
MSMF	VMF, AVMF	Effectively preserve thin lines, fine details and image edges
FBDA	SMF	Power of noise detection and eliminate corrupted pixels during filtering
DAWSMF	HEIND, Weighted Median	Retains the edge information for high density impulse noise
SAWMF	WMF	• Best smoothing effect • Better image quality • Robust
SWVMF	WVMF	Improves the performance in both detail preservation and noise suppression
MDWF	DWMF	• Capable of noise suppression and image detail preservation • Reduces computational complexity and enhances efficiency
IAFF	AFF, WMF	Restores meaningful image detail at high levels of corruption
ASMD-DPR	ASWM, EPR	Significantly superior both visually and quantitatively with high noise level
FDF	AVMF, MSMF	Significantly superior both visually and quantitatively
FWMA	WMF	Surpasses even at very high densities
AFIDM	CWM, SWM, AMED, AWMF, DWM, FRDMF	Superior in noise removal and detail preservation
TSQSVF	WVMF	• Superbly curb impulse noise • Shows performance improvements
MIVMF	VMF	• Preserve edge details • Attain better-quality noise reduction
CAVMFWMF	AVMF, Weighted Mean, NCLP-VMF	• Provides improved performance for SAP and RVIN • Increased computational complexity
LRDQSF	WVMF	Lower false and miss detection rate
RAFF	MMV Detection, Modified Fuzzy Filter	Effectively restore both image details and edge information
DAMF	Matrix and Decision based	Successfully removed SAP noise at all densities
BPDF	Median (Maximum repetitive pixel values)	• Removes SAP noise • Succeeded more in medium noise density
ASWMF	3σ principle and local intensity statistics.	• Performs superiorly in presence of impulses • No significant superiority in computational time
TSF	Median	• Works effectively for various noise levels • Non-iterative • Perform very fast
RSAMF	Switching MF	• Best performance in visual inspection • Need improvements for high level of noise

MSVMAF	MHFC	• Better for low and high noise levels • Image details are maintained significantly
AWQDF	CDM, ROR, LRD, WVMF	• Longer running time • Much competitive in denoising performance
FAPGF	Peer Group, WA	• Preserves tiny image details • Performs well for strong impulsive noise • Low computational complexity
DLSF	DNN, FAMF	• Performs well on images with artificial impulsive noise and real noise • Keeping the undistorted pixels unchanged • Quite fast • No adjusting parameters
MF-DnCNN	MFs, RLDCNN	Remove both Gaussian and SAP noises from the image
MWMF	WMF	Performs well for low SAP noise density
MDFMF	FDMF	Works well for low and high SAP noise densities

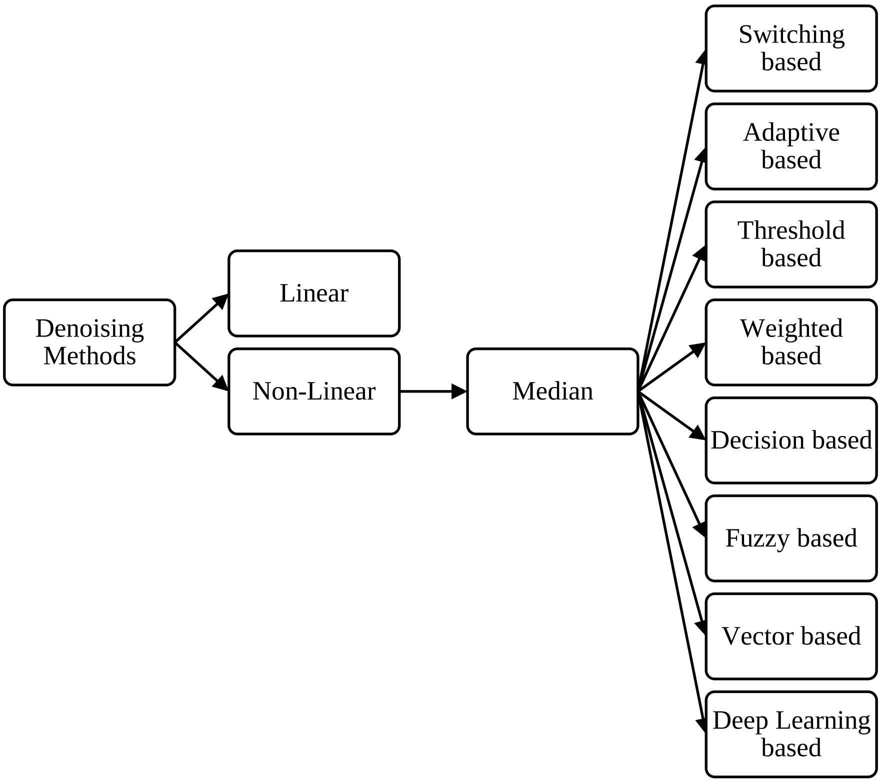


Fig.1. Classification of Median Filter Variants

Before the discussion of various median filter variants, Simple Median Filter (SMF) is described as:

2.1 STANDARD MEDIAN FILTER (SMF)

SMF [4], a nonlinear approach for impulse noise reduction, is used as a preprocessing tool to enhance the degraded image quality for post-processing. The concept is swapping of median and central pixel of processing window of 5×5 or 3×3 or any other size. The computing pixel can be either 255, 0 or any another value from 0 to 255. The handling of all pixels with the same technique, if affected or not, is a major error in this process. The median filter also struggles to keep edges.

2.2 MEDIAN FILTER VARIANTS

2.2.1 Center Weighted Median Filter (CWMF):

CWMF [5], a weighted median filter where only the central pixel of the filter has a weight greater than 1 is studied. The likelihood of choosing central value as the restorative value is greater than that of the other pixels by assigning so. This filter will retain image information while eliminating additive white and impulsive noise. An adaptive CWMF (ACWMF) with a space of varying central weight is proposed in an attempt to improve the efficiency of CWMF. It is demonstrated that the ACWMF can remove signal-dependent as well as signal-independent noise.

2.2.2 Vector Median Filter (VMF):

The vector median operations were assessed using maximum likelihood estimation method, with a constraint that one of input vectors is chosen as output. The VMFs [6] process vector-valued signal samples, which have been shown as advantageous over component-wise processing. The VMFs exhibited properties similar to median filter, such as suppression of impulses and the preservation of signal edges.

2.2.3 Directional Weighted Median Filter (DWMF):

A new median-based filter, DWMF [7] is suggested to eliminate random impulse noise. To weight the pixels in a local window, this method measured the neighbor information of the centre pixel in four directions. A noise infected pixel could be detected and eliminated in optimal direction by the weighted median filter. It employs use of impulse and edge properties for detection and reduction of noise. The simulation results show that DWMF outperforms many current median dependent filters in subjective and objective evaluations.

2.2.4 Fuzzy Switching Median Filter (FSMF):

A recursive FSMF [8], was introduced by using a fuzzy inference mechanism which is made up of two semi-independent modules: SAP noise detection and fuzzy noise cancellation. The basis of SAP noise detection algorithm is that when measuring the noisy image histogram, an image corrupted by SAP noise with probability p will generate two peaks for intensities 0 and 255 and will then begin searching the noisy image for two intensities of noise pulses. When these two are detected, the filtering operation will proceed by windowing operation on noisy image from the top left to bottom right corner. Simulation findings demonstrate that FSMF can eliminate noise while retaining image information and textures very well.

2.2.5 Fuzzy Reasoning based Directional Median Filter (FRDM):

A novel, Fuzzy Reasoning-based Directional Median (FRDM) filter [9] is proposed for the efficient elimination of RVIN. The variations between the current pixel and the neighbors associated with the four edge directions are added to the fuzzy reasoning technique in the proposed filter, defining the current pixel as one of three types: impulse noise pixel, informative pixel, or noise free pixel. With the acquired knowledge on the direction of the edge, the proposed filter will eliminate the noise of the impulse and simultaneously retain the detail.

2.2.6 Noise Adaptive Fuzzy Switching Median Filter (NAFSM):

A novel two-stage noise adaptive fuzzy switching median (NAFSM) filter [10] for detecting and eliminating SAP noise is introduced. The identification stage would initially use the corrupted image histogram to classify noise pixels. The observed noise pixels then exposed to second stage of filtering action, while the noise-free pixels will be preserved. The filtering mechanism of NAFSM then uses fuzzy logic to resolve the ambiguity as introduced by noise present in the derived local information.

2.2.7 Modified Switching Median Filter (MSMF):

MSMF [11] presented to eliminate SAP noise in color images, is a two-step noise detector: An adaptive VMF detection method is in use to discover pixels that are noise candidates in the first step; these noise candidates are judged by use of four one-dimensional Laplacian operators that retained edge pixels in the second step. In specific, the proposed solution will efficiently retain thin lines, fine detail and image edges.

2.2.8 Fuzzy Based Decision Algorithm (FBDA):

FBDA [12] is a fuzzy-based median filter that computes the difference for each pixel in the chosen window based on corrupted pixel and then computes the membership value for each pixel based on the largest difference. After that, the algorithm extracts from the window pixels with extremely high and extremely low membership values, which could represent impulse noise. After that, SMF is applied to the remaining pixels to return the value to the current pixel location in the window.

2.2.9 Direction based adaptive weighted switching median filter (DAWSMF):

An effective direction based adaptive weighted switching median filter (DAWSMF) [13] for the restoration of high-density impulse noise polluted images was proposed. Its filtering process consists of the identification phase and the filtering phase. The identification step of the proposed approach uses the histogram estimation impulse noise detection algorithm. The filtering algorithm is applied to the pixels detected after detecting noisy pixel locations in the image. In the filter window, noisy pixels are replaced by a weighted median value of uncorrupted pixels. The weight value given depends on the proximity of each uncorrupted pixel to central corrupted pixel in the current filter window.

2.2.10 Selective Adaptive Weighted Median Filter (SAWMF):

A new impulsive noise reduction algorithm is introduced, the Selective Adaptive Weighted Median Filter (SAWMF) [14] that implements a switching feature. The new algorithm employs a weighted median filter with weights modified from two fixed values to recover the observed noisy pixels while leaving the noise-free pixels alone, using a median-based contrast technique to determine whether an image pixel is an impulse or a noise-free one.

2.2.11 Switching Weighted Vector Median Filter (SWVMF):

A new vector median filter [15] based on fuzzy noise detection and image edge detection was proposed to eliminate impulse noise in the color image. The pixels in the noised image are compared to the corresponding pixels in the reference image, which is filtered by applying a scalar median filter to each noised image channel during the noise detection phase. The similarity of pixels is used to determine whether or not they are corrupted. A weighting method based on pixel position data is proposed. In this step, the pixels in the filter window are assigned different weights according to their distributed classes, which are categorized on the basis of image edge detection. Quantitative measurements and filtered images suggest that the proposed approach produces more successful performance relative to traditional approaches.

2.2.12 Modified Directional Weighted Filter (MDWF):

A novel directional weighted filter [16] algorithm for eliminating SAP noise is suggested after a detailed review of the shortcomings of Directional Weighted Median Filter (DWMF) and Modified Directional Weighted Median (MDWM). The suggested algorithm first computes the noise intensity of each noise pixel's non-recursive local window, followed by an adaptive computation of the weighted grey level mean of the recursive or non-recursive filter window to return the current noise pixel to the noise density. This eliminates the detrimental consequences of noise neighbors and the harmful optimal path in both DWM and MDWM concurrently. This algorithm greatly improves the ability to suppress noise and retain image information, particularly when the noise density is high.

2.2.13 Iterative Adaptive Fuzzy Filter Using Alpha-Trimmed Mean (IAFF):

Presented a novel two-stage filter [17] for denoising images corrupted by SAP noise. In the first step, an adaptive fuzzy filter is used to detect noisy pixels. In the second step, denoising is conducted on noisy pixels, performing a weighted mean filtering procedure on neighboring uncorrupt pixels.

2.2.14 Adaptive Switching Median Detector with Detail Preserving Regularization (ASMD-DPR):

A two-phase scheme [18] is presented to eliminate RVIN, whether or not the noise level is low. To be more specific, an adaptive switching median filter or an adaptive non-local switching median filter is used to classify noise candidates in the first step. The edge-preserving regularisation process is used to restore only the values of the noise candidates in the second step.

2.2.15 Fuzzy Decision Filter (FDF):

By changing MSMF, a fuzzy decision filter (FDF) [19] is proposed wherein fuzzy membership is inserted into noise detection. In reality, it is using a soft threshold instead of agreeing – refusing a decision. This requires more facts than a binary judgment to be used. In the second level, the noise candidate calculates the memberships that belong to the noise-free party. The algorithm retains the advantages of switching vector filters and improves the accuracy of the pixels that are classified.

2.2.16 Fuzzy Weighted Mean Aggregation (FWMA):

A fuzzy weighted mean aggregation (FWMA) [20] algorithm is proposed to eliminate SAP noise and RVIN from the images. A fuzzy weighted mean aggregation is used to create Interval-Valued Fuzzy Relations (IVFR) for detecting the pixel as noisy or not. At the training point to reduce the error of image noise detection, the authors derived the iterative learning process of the weighting parameters. In addition, the training algorithm implements the pocket learning mechanism to choose best parameter range for noise pixel detection. At the test point, a filtering approach is proposed that incorporates an impulse noise detector with a weighted average filter to eliminate impulsive noise. Simulation findings show that the proposed algorithm performs well at a very high noise density of 97%.

2.2.17 Adaptive Fuzzy Inference System based Directional Median Filter (AFIDM):

A novel method known as the adaptive fuzzy inference system based directional median filter (AFIDM) [21] is proposed. The noise detector is based on an adaptive fuzzy inference system, which provides accurate classification of noisy pixels in both smooth and detailed areas. This classification results in a thorough preservation noise filtering process. Following that, median and directional median filters-based noise adaptive filtering is performed using the noise detector's information.

2.2.18 Two Stage Quaternion Switching Vector Filter (TSQSVF):

A new two stage quaternion switching vector filter (TSQSVF) [22] to remove impulse noise from color images has been proposed that combines brightness and chrominance differences to measure color distances between color pixels. The impulse detection module determines whether or not a pixel is noisy by using pixels in four directions in two stages. The image pixels are classified as noise-free or potentially noisy in the first stage. Only the potentially noisy pixels require further investigation. Potentially noisy pixels are further judged to be noisy or not by looking for direction with the greatest number of identical pixels in the second stage. Finally, to eliminate impulse noise, a weighted VMF is performed only at the observed noisy locations.

2.2.19 Moran's I Vector Median Filter (MIVMF):

An approach based on Moran's I (MI) statistic to impulse noise detection and elimination in color images is proposed [23] known as the Moran's I vector median filter (MIVMF). The detection module can be used to determine whether a pixel is noise-free or not. VMF will be used to remove the noise if the pixel is noisy. This detection capability is based on switching mechanism, which selects noisy pixels to denoise and thus shortens processing time by reducing the number of vector calculations in the VMF. This is accomplished through the MI index and the indication of one-dimensional Laplacian kernels.

2.2.20 Combination of Adaptive Vector Median Filter and Weighted Mean Filter (CAVMFWMF):

A new technique for removing impulse noise from colour images is proposed [24]. Non-causal linear prediction error is combined with a deviation-based criterion to detect noisy and good pixels. During the noise removal procedure, CAVMFWMF is thus applied to both noisy and non-noisy pixels. For a noisy pixel, the adaptive VMF is applied to the pixel, with the window size changing based on the availability of good pixels. A non-noisy pixel, on the other hand, is replaced by the weighted mean of the good pixels in the processing window.

2.2.21 Quaternion Switching Vector Median Filter Based on Local Reachability Density (LRDQSF):

An efficient color impulse detector is presented to improve detection precision [25]. It is proposed to develop a new colour distance metric based on quaternion theory. The suggested colour distance metric is used to calculate the pixel's local colour density. To determine whether or not a colour pixel is corrupted by impulse noise, a hard thresholding technique is used. A weighted VMF would be used to restore the observed noisy pixels, while the noise-free pixels would remain unchanged.

2.2.22 Region Adaptive Fuzzy Filter (RAFF):

An adaptive fuzzy filter [26] for the elimination of RVIN from color images is proposed. For better recognition of noisy and non-noisy pixels, an improved minimum mean value identification mechanism is proposed. The modified fuzzy filter takes into account the association between the colour channels and recursively adapts to the local noise level. This filter uses an adaptation strategy to determine the actual permissible size of the window used during fuzzification and filtering. Instead of an effective filtering step that has the potential to miss information, the selective second iteration of the filter is added to heavily distorted regions in order to retain further image data.

2.2.23 Different Applied Median Filter (DAMF):

A new approach was proposed, Different Applied Median Filter (DAMF) [27], to eliminate SAP noise at all densities. The DAMF uses noise-free pixels in an adaptive-size neighbourhood to remove noise, and previously processed pixels to remove residual noises. It is demonstrated that DAMF could effectively eliminate SAP noise at all densities.

2.2.24 Basic Pixel Density Filter (BPDF):

A new technique for eliminating SAP noise was presented, referred to as basic pixel density filter (BPDF) [28]. The first step is to determine whether the pixel is noisy, followed by selecting an adaptive window size that recognizes the noisy pixel as the central. The current pixel value is set to the window's most repetitive noiseless pixel value. The results show that BPDF performs better at low and medium noise densities.

2.2.25 Adaptive Sequentially Weighted Median Filter (ASWMF):

An ASWMF method [29] for image recovery from impulse noise that includes a simple and efficient noise detector as well as a noise reduction technique capable of completely eliminating impulse noise while retaining structure and edge information. The ASWMF noise detector fully exploits the three principles of regular distribution and local amplitude statistics; and the ASWMF noise reduction strategy is assisted by the adaptive, sequentially weighted median processing. They together make denoising efficiency substantially better.

2.2.26 Two-Stage Filter (TSF):

The suggested approach [30] is divided into two stages: the first removes high-density noise based on the median of the weakly initial pixels, and the second reduces low-density noise based on the median of the highest repeated pixel values. Maximum repeated pixel values are more effective than weakly initialised pixels at reducing low-density noise. In case of high-density noise, however, the median of weakly original pixels does not reliably represent the meaning of distorted pixels. It is also important to convert from high-density to low-density noise for applying a median of maximum repeated pixel values.

2.2.27 Recursive Switching Adaptive Median Filter (RSAMF):

The feasibility of improving the performance of the recursive median filter by adapting it to switching and adaptive approaches is investigated, and this scheme is referred to as the Recursive Switching Adaptive Median Filter (RSAMF) [31]. The process is divided into two stages, namely the identification of noise and the restoration of noise. SAP pixel candidates are detected at the noise detection level. Then, at the point of reconstruction, an adaptive approach is used for restoration. The filter size will be increased until the window identifies at least eight noise-free pixel candidates. Because of the recursive approach, the noise mask is changed each time it is restored.

2.2.28 Multiclass Support Vector Machine based Adaptive Filter (MSVMAF):

A multiclass support vector machine (SVM) based adaptive filter (MSVMAF) [32] for removal of impulse noise from color images is proposed. During this analysis, the feature set consisting of a prediction error, a difference between the median value and the centre pixel; the median value in the kernel under operation was used. An adaptive window-based filter is used to process each pixel of the test image, which is dependent on the class assigned to the testing phase. The baseline system has been designed using modified histogram based fuzzy color filter (MHFC) technique.

2.2.29 Adaptive Weighted Quaternion Color Distance Filter (AWQDF):

An adaptive weighted quaternion color distance filter (AWQDF) [33] is proposed based on the new color distance measure, robust outlyingness ratio (ROR) and local reachability density (LRD), which are defined in grayscale images to implement a coarse-to-fine color noise detection operator are extended to color images. In noise filtering, a weighted VMF is in use to restore the pixels judged as noisy.

2.2.30 Fast Averaging Peer Group Filter (FAPGF):

A novel method for removing impulsive noise in colour images is presented [34], which is based on the idea of expressing the degree of membership of the central pixel to the local neighbourhood by the size of its peer group. This filter's structure is divided into pixel inspection and replacement parts. The first assesses how well the central pixel of the local window belongs to its surroundings, and the second employs the Weighed Average Filter (WAF) to replace pixels identified as outliers. The WAF weights are calculated by examining the size of the peer groups of samples that are close to the processed pixel.

2.2.31 Deep Learning based Switching Filter (DLSF):

A switching filter [35] based on a deep neural network is proposed for removing impulsive noise in colour images. To distinguish noise-free pixels from impulses, a sigmoid layer is added, and the residual learning problem is reformulated. Because of its good balance of computational complexity and restoration efficacy, the deep neural network is used as the impulse detector, and the corrupted pixels are restored using an adaptive mean filter. The proposed filtering architecture detects impulsive pixels by a modified Denoising Convolutional Neural Network (DnCNN) and restores them using an adaptive mean filter.

2.2.32 Median filters combined with denoising convolutional neural network (MF-DnCNN):

A new filter, median filters combined with convolutional neural networks for gaussian and SAP noises, is proposed for the elimination of combined gaussian and impulse noises [36]. The removal of gaussian and impulse noise took two steps. Impulse noise is first detected, followed by noise rejection using 3×3 and 5×5 window size median filters. The residual learning Denoising Convolutional Neural Network (DnCNN) is used to remove gaussian noise in the second step.

2.2.33 Modified Weighted Median Filter (MWMF):

After thoroughly examining the causes of the deficiencies in the existing filtering methods, a modified weighted median filter (MWMF) method [37] for colour images corrupted by SAP noise is proposed. A pixel in an 8-bit image is classified as either noise free pixel or noise pixel by comparing the extreme values of the centre pixel in the current filtering window (0 or 255). The detected noise pixels are influenced by directional differences and the number of good pixels in the current filtering window during the noise filtering step.

2.2.34 Modified Directional and Fuzzy based Median Filter (MDFMF):

A modified directional and fuzzy based median method [38] for filtering color images that are SPN corrupted is proposed using noise detection, noise filtering and restoration of noise free image. Noise detection is carried out to classify the pixels as noise or noise-free depending upon the intensity values. The detected noise pixels are subjected to noise filtering in which they are updated to fuzzy based median values of the good pixels number in current taken filtering window depending upon the minimum or maximum directional differences sorted values in all the twelve directions and are restored.

3. COMPARISON BASED ON RELATIVE PERFORMANCE

In this section, comparison of de-noising filters is done based on relative performance for both SAP noise and RVIN. A number of simulations are performed on a standard set of images. Selective SAP noise and RVIN levels have been applied to the standard images and then analyzed by employing different filters. The quality of each processed image is assessed using MATLAB R2013a against a set of quality measurement metrics, which are as follows:

- ***Peak Signal-to-Noise Ratio (PSNR)***: This metric measures the signal-to-noise ratio of the decibels and is widely used to determine the quality of the image being refined over the original image. Higher values equal higher efficiency, and vice versa. Mathematically, PSNR is:

$$PSNR = 10\log\frac{R^2}{MSE} \tag{1}$$

where R is the maximum variation in the image data type and MSE is the mean square error.

- ***Structural Similarity Index Measure (SSIM)***: This is a Human Visual System (HVS) inspired metric which ranges the quality of an image from -1 to 1. It is calculated as follow:

$$SSIM = \frac{\left(2\overline{xy}+C_1\right)\left(2\sigma xy+C_2\right)}{\left(\overline{x}^2+\overline{y}^2+C_1\right)\left(\sigma x^2+\sigma y^2+C_2\right)} \tag{2}$$

Constants C_1= 0.01 and C_2 = 0.03 are standard empirical choices for this measure.

- ***Normalized Mean Square Error (NMSE)***: The Normalized Mean Square Error (NMSE) is the metric to measure the normalized average error of the restored image contrary to the original. Essentially, it measures the mean squared error between the expected values and the initial intensities of the corresponding pixels after normalizing them into the interval [0, 1]. The mathematical formulation for MSE is:

$$NMSE = \frac{\sum_{i=1}^{m}\sum_{j=1}^{n}\left\|x(i,j)-y(i,j)\right\|_2^2}{\sum_{i=1}^{m}\sum_{j=1}^{n}\left\|x(i,j)\right\|_2^2} \tag{3}$$

Here m×n is the image dimensions, $x(i,j)$ is the original image and $y(i,j)$ is the refined image.

3.1 COMPARISON FOR SAP NOISE

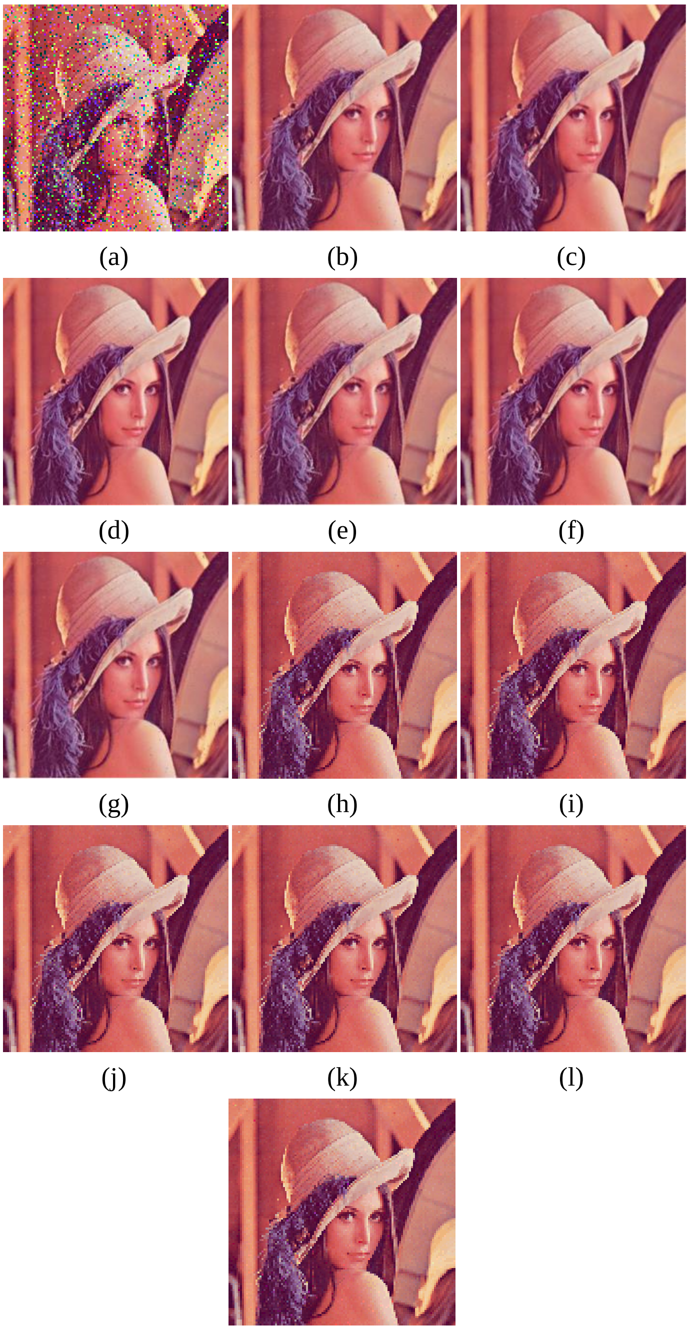
Lena and Peppers Image are chosen to be the source image dataset as given in Fig.2 in order to make a comparison for SAP noise, so as to reflect acceptable amount of diversity in the image content's complexity.

(a) (b)

Fig.2 Source Image Dataset consisting of: (a) Lena Image and (b) Peppers Image

The resolution of the images is 512×512.The comparison for SAP noise is done for different de-noising methods taken into consideration such as VMF [6], FAPGF [35], TSQSVF [22], MIVMF [23], LRDQSF [25], AWQDF [34], MWMF [38], MSVMAF [32], NAFSM [10], DAMF [27], BPDF [28] and MDFMF [39] with regard to subjective and objective analysis. On the basis of visual results as revealed in Fig.3 at 10% noise on Lena image, it is observed that the filters MSVMAF and MDFMF has re-established the corrupted images with superior edge information and enhanced image details. Additionally, the shiny lustre is also being reserved in a better way, in comparison to other prevailing filters.

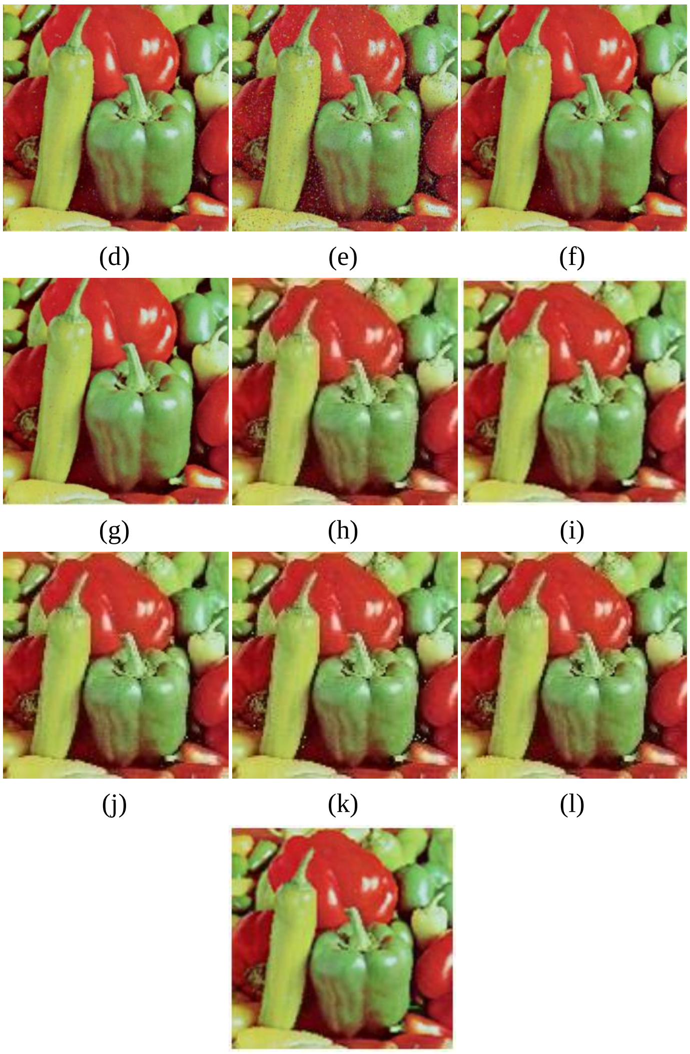
The Fig.4 shows the visual comparison of different denoising filters for Peppers image with 25% SAP noise. The Table.2 and Table.3 shows PSNR and SSIM results for test images Lena and Peppers degraded by 10%, 40% and 80% SAP noise levels for different de-noising methods taken into consideration: VMF [6], FAPGF [35], TSQSVF [22], MIVMF [23], LRDQSF [25], AWQDF [34], MWMF [38], MSVMAF [32], NAFSM [10], DAMF [27], BPDF [28] and MDFMF [39]. It can be seen from Table.2 that there is a noteworthy enhancement in the performance of the restoration using MSVMAF, NAFSM, DAMF, BPDF and MDFMF filters when noise level is greater than 40%.



(a) (b) (c) (d) (e) (f) (g) (h) (i) (j) (k) (l) (m)

Fig.3. Lena (a) Image with 10% noise (b) VMF [6], (c) FAPGF [35], (d) TSQSVF [22], (e) MIVMF [23], (f) LRDQSF [25], (g) AWQDF [34], (h) MWMF [38], (i) MSVMAF [32], (j) NAFSM [10], (k) DAMF [27], (l) BPDF [28] and (m) MDFMF [39]

(a) (b) (c)



(d) (e) (f) (g) (h) (i) (j) (k) (l) (m)

Fig.4. Peppers (a) Image with 25% noise (b) VMF [6], (c) FAPGF [35], (d) TSQSVF [22], (e) MIVMF [23], (f) LRDQSF [25], (g) AWQDF [34], (h) MWMF [38], (i) MSVMAF [32], (j) NAFSM [10], (k) DAMF [27], (l) BPDF [28] and (m) MDFMF [39]

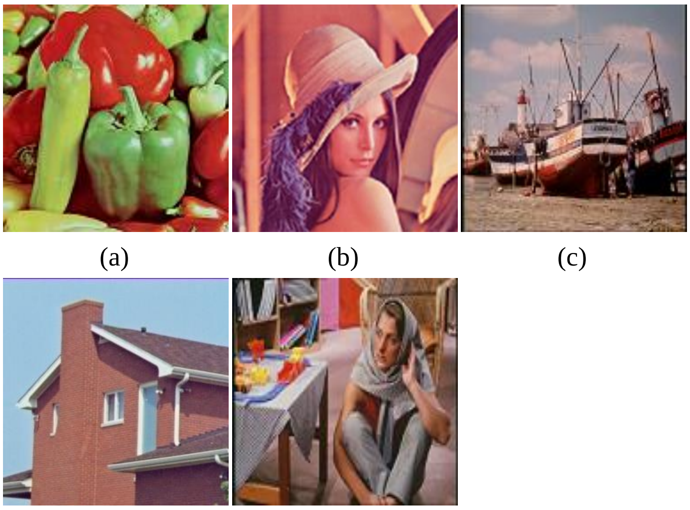
Table.2. PSNR values of color test images degraded by different SAP noise levels for the de-noising methods considered

De-noising Methods	Noise level (%)	Lena	Peppers
VMF [6]	10	30.81	29.77
	40	19.17	18.68
	80	8.76	7.86
FAPGF [35]	10	32.02	30.58
	40	25.52	24.45
	80	10.87	9.56
TSQSVF [22]	10	33.30	30.31
	40	24.56	23.67
	80	8.21	7.43

MIVMF [23]	10	31.17	29.88
	40	20.24	21.54
	80	6.78	7.36
LRDQSF [25]	10	33.58	29.97
	40	24.94	22.76
	80	8.79	7.98
AWQDF [34]	10	34.61	30.14
	40	25.62	24.88
	80	9.88	8.88
MWMF [38]	10	37.69	30.43
	40	30.68	27.45
	80	22.66	20.78
MSVMAF [32]	10	42.31	41.98
	40	34.13	32.39
	80	20.02	19.11
NAFSM [10]	10	37.94	30.39
	40	32.87	27.23
	80	26.75	22.44
DAMF [27]	10	40.83	31.00
	40	33.54	27.65
	80	27.76	23.10
BPDF [28]	10	38.02	31.19
	40	30.28	26.91
	80	19.85	16.26
MDFMF [39]	10	43.04	42.72
	40	36.66	35.89
	80	34.27	34.98

Table.3. SSIM values of color test images degraded by different SAP noise levels for the de-noising methods considered

De-noising Methods	Noise level (%)	Lena	Peppers
VMF [6]	10	0.87	0.67
	40	0.55	0.45
	80	0.26	0.22
FAPGF [35]	10	0.93	0.83
	40	0.75	0.65
	80	0.34	0.42
TSQSVF [22]	10	0.93	0.83
	40	0.71	0.61
	80	0.21	0.11
MIVMF [23]	10	0.89	0.79
	40	0.43	0.63
	80	0.01	0.09
LRDQSF [25]	10	0.94	0.84
	40	0.75	0.65
	80	0.29	0.26
AWQDF [34]	10	0.95	0.94
	40	0.77	0.76
	80	0.38	0.36
MWMF [38]	10	0.98	0.96
	40	0.93	0.89
	80	0.79	0.67
MSVMAF [32]	10	0.97	0.97
	40	0.95	0.78
	80	0.52	0.51
NAFSM [10]	10	0.98	0.95
	40	0.95	0.82
	80	0.79	0.69
DAMF [27]	10	0.99	0.98
	40	0.96	0.91
	80	0.73	0.71
BPDF [28]	10	0.98	0.96
	40	0.79	0.79
	80	0.32	0.50
MDFMF [39]	10	0.99	0.97
	40	0.88	0.80
	80	0.82	0.67



(a) (b) (c)

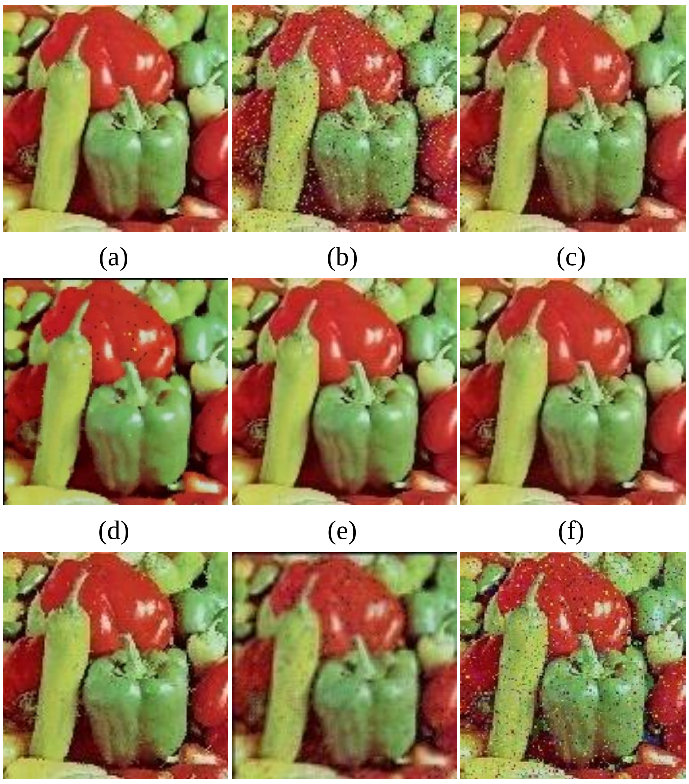
(d) (e)

Fig.5. Considered test images (a) Peppers (b) Lena (c) Boat (d) House (e) Barbara

The images restored from MSVMAF, NAFSM, DAMF, BPDF and MDFMF filters provide perceptually more similarity with original images, in comparison to the other considered filters output as can be observed from Table.3.

3.2 COMPARISON FOR RANDOM VALUED IMPULSE NOISE (RVIN)

In order to make a comparison for RVIN, Lena Image, Peppers Image, Boat Image, House Image and Barbara Image are chosen to be the source image dataset as given in Fig.5 so as to reflect acceptable amount of diversity in the image content's complexity. The resolution of these images is 512×512.The comparison for random valued impulse noise is done for different de-noising methods taken into consideration such as SAWMF [14], MSMF [11], VMF [6], SWVMF [15], CAVMFWMF [24], FDF [19] and BPDF [28] with regard to subjective and objective analysis.



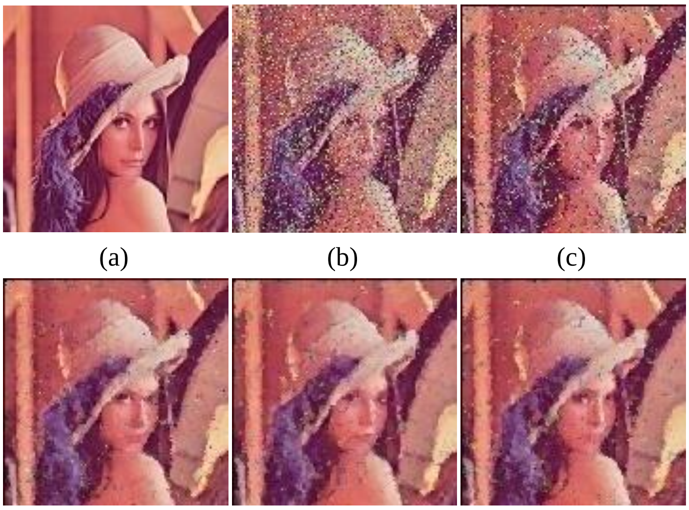
(a) (b) (c)

(d) (e) (f)

(g) (h) (i)

Fig.6. Peppers Image (a) Input, (b) Image with 10% noise (c) SAWMF [14], (d) MSMF [11], (e) VMF [6], (f) SWVMF [15], (g) CAVMFWMF [24], (h) FDF [19] and (i) BPDF [28]

The visual outputs of various images corrupted by different RVIN levels are given in Fig.6 to Fig.8. The visuals of Peppers Image with 10% random impulse noise for various denoising filters taken for comparison are shown in Fig.6.

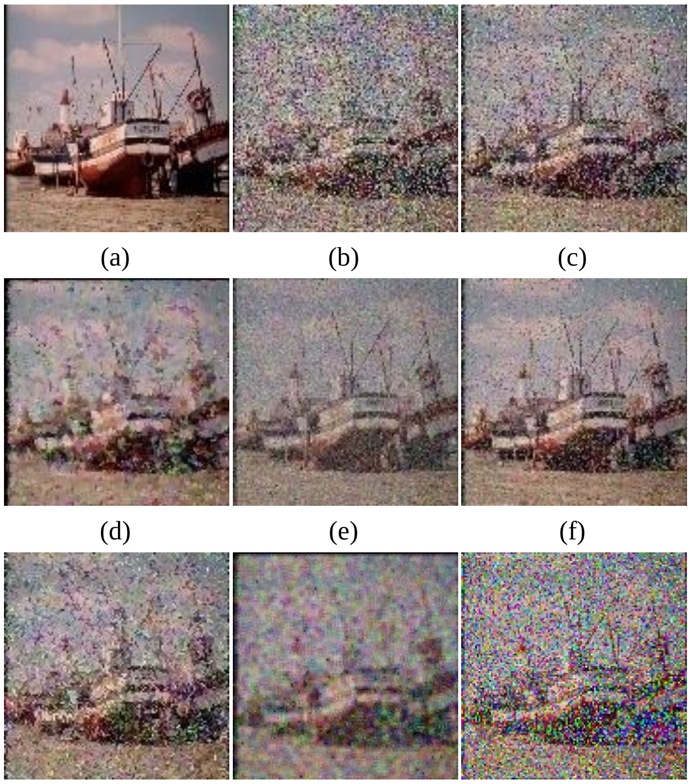


(a) (b) (c)

(d) (e) (f)

(g) (h) (i)

Fig.7. Lena Image (a) Input, (b) Image with 30% noise (c) SAWMF [14], (d) MSMF [11], (e) VMF [6], (f) SWVMF [15], (g) CAVMFWMF [24], (h) FDF [19] and (i) BPDF [28]



(a) (b) (c)

(d) (e) (f)

(g) (h) (i)

Fig.8. Boat Image (a) Input, (b) Image with 50% noise (c) SAWMF [14], (d) MSMF [11], (e)VMF [6], (f) SWVMF [15], (g) CAVMFWMF [24], (h) FDF [19] and (i) BPDF [28]

The filters VMF, SWVMF and CAVMFWMF have restored the corrupted image with improved image details as can be observed from Fig.6. It may also be observed that there is certain high frequency and edge distortions visible in FDF. The Fig.7 shows the visuals of Lena Image corrupted by 30% random impulse noise for various denoising filters taken for comparison. From Fig.7, it can be seen that although noise is reduced to a great extent but high frequency and edge distortions are still there in the restored image at 30% random noise level.

The Fig.8 shows the visuals of Boat Image with 50% RVIN for various denoising filters taken for comparison. The results of PSNR, SSIM, NMSE and Computation Time values of test images with RVIN levels 10%, 30 % and 50% for various de-noising filters: SAWMF [14], MSMF [11], VMF [6], SWVMF [15], CAVMFWMF [24], FDF [19] and BPDF [28] taken are tabulated in Table.4 to Table.7. The Table.4 demonstrates that the CAVMFWMF offers better performance with regard to PSNR. CAVMFWMF also shows better functioning with regard to SSIM throughout the varied random noise level as can be seen from Table.5.

It can be noted from Table.6 that of all the filters, CAVMFWMF provides better NMSE at 10% random noise for all the color images taken for comparison. As random noise level increases i.e. at 30% noise, SWVMF gives better NMSE for Peppers image, VMF has better NMSE for Lena image, CAVMFWMF has better NMSE for Boat, House and Barbara images. At higher noise level i.e. at 50% noise, VMF gives better NMSE for Peppers image, SWVMF has better NMSE for Lena and Boat images, CAVMFWMF has better NMSE for House image and FDF has better NMSE for Barbara image of all the filters. Among all the filters, BPDF is computationally efficient as can be seen from Table.7 for Peppers, Lena, Boat and Barbara images.

Table.4. PSNR results of test images with RVIN levels 10%, 30 % and 50% for taken de-noising methods

Image Name	**Noise levels**	**De-noising Methods**						
		SAWMF [14]	**MSMF [11]**	**VMF [6]**	**SWVMF [15]**	**FDF [19]**	**CAVMFWMF [24]**	**BPDF [28]**
Peppers	10	38.08	40.26	40.03	39.83	41.40	48.65	40.47
	30	32.17	38.35	38.02	38.74	36.39	34.72	30.41
	50	26.86	33.82	33.40	33.46	32.47	27.29	25.24
Lena	10	40.33	43.15	43.61	43.40	44.17	50.53	43.03
	30	34.06	41.40	41.61	41.75	39.46	37.72	32.20
	50	28.68	36.03	35.97	36.07	35.24	29.19	26.99
Boat	10	37.50	40.45	41.31	41.25	42.17	46.65	41.69
	30	32.74	38.92	39.52	39.45	38.46	36.56	31.31
	50	28.72	34.96	35.17	35.06	34.82	28.72	26.34
House	10	38.22	41.08	41.85	41.72	42.30	57.30	43.14
	30	33.01	39.22	39.81	39.76	38.99	38.46	32.50
	50	28.64	35.56	35.45	35.86	35.76	29.63	27.44
Barbara	10	37.56	40.13	40.70	40.40	42.09	49.85	42.74
	30	32.91	39.18	38.67	39.02	38.59	36.29	31.71
	50	28.32	35.44	35.16	35.20	35.05	28.95	26.90

Table.5. SSIM results of test images with RVIN levels 10%, 30 % and 50% for taken de-noising methods

Image Name	**Noise levels**	**De-noising Methods**						
		SAWMF [14]	**MSMF [11]**	**VMF [6]**	**SWVMF [15]**	**FDF [19]**	**CAVMFWMF [24]**	**BPDF [28]**
Peppers	10	0.5040	0.6103	0.6090	0.6045	0.5786	0.8307	0.7746
	30	0.3387	0.5196	0.5087	0.4794	0.4295	0.5325	0.5381
	50	0.2329	0.4702	0.3965	0.3448	0.2736	0.3841	0.3665
Lena	10	0.3206	0.4149	0.4269	0.4949	0.5618	0.8744	0.8548
	30	0.2909	0.3475	0.3547	0.4274	0.3747	0.5749	0.4650
	50	0.1554	0.3278	0.3354	0.3739	0.2724	0.3822	0.2303
Boat	10	0.2688	0.4014	0.4734	0.4597	0.5309	0.9382	0.8132
	30	0.1974	0.3241	0.3368	0.3296	0.3435	0.6498	0.5247
	50	0.1862	0.2851	0.2984	0.2704	0.2637	0.3571	0.3857
House	10	0.3490	0.5797	0.5812	0.5483	0.5598	0.8356	0.6211
	30	0.2360	0.5040	0.5463	0.5251	0.4847	0.4650	0.3266
	50	0.1014	0.3004	0.2987	0.3104	0.2903	0.1444	0.2114
Barbara	10	0.4411	0.5899	0.6262	0.6163	0.6174	0.8706	0.2306
	30	0.2790	0.5441	0.5734	0.5819	0.3618	0.3592	0.1368
	50	0.1107	0.3247	0.3178	0.3589	0.1956	0.1305	0.0534

Table.6. NMSE results of test images with RVIN levels 10%, 30 % and 50% for taken de-noising methods

Image Name	Noise levels	De-noising Methods						
		SAWMF [14]	MSMF [11]	VMF [6]	SWVMF [15]	FDF [19]	CAVMFWMF [24]	BPDF [28]
Peppers	10	0.0954	0.0725	0.0687	0.0703	0.0621	0.0206	0.0731
	30	0.1712	0.0885	0.0852	0.0847	0.0970	0.1058	0.1999
	50	0.2469	0.1505	0.1419	0.1442	0.1505	0.2732	0.3354
Lena	10	0.0568	0.0441	0.0424	0.0432	0.0393	0.0126	0.0449
	30	0.1123	0.0539	0.0516	0.0524	0.0631	0.0537	0.1325
	50	0.1893	0.0918	0.0895	0.0878	0.0962	0.1377	0.2230
Boat	10	0.0648	0.0627	0.0580	0.0586	0.0526	0.0193	0.0557
	30	0.1331	0.0710	0.0687	0.0720	0.0761	0.0584	0.1572
	50	0.2124	0.1093	0.1092	0.1046	0.1074	0.1405	0.2585
House	10	0.0649	0.0627	0.0585	0.0592	0.0558	0.0040	0.0384
	30	0.1384	0.0746	0.0713	0.0709	0.0773	0.0349	0.1113
	50	0.1977	0.1127	0.1088	0.1104	0.1092	0.0968	0.1846
Barbara	10	0.1050	0.0774	0.0740	0.0762	0.0636	0.0165	0.0618
	30	0.1686	0.0882	0.0873	0.0875	0.0900	0.0706	0.1861
	50	0.2548	0.1296	0.1330	0.1326	0.1294	0.1685	0.3010

Table.7. Computation Time (s) of test images with RVIN levels 10%, 30 % and 50% for taken de-noising methods

Image Name	Noise levels	De-noising Methods						
		SAWMF [14]	MSMF [11]	VMF [6]	SWVMF [15]	FDF [19]	CAVMFWMF [24]	BPDF [28]
Peppers	10	14.9620	97.8638	19.9843	36.4189	86.0107	8.7831	1.2525
	30	16.5254	105.0508	20.8559	63.3598	89.5663	8.2876	2.4906
	50	8.8638	118.0507	21.5156	62.7693	87.7243	8.2292	3.8465
Lena	10	10.4017	102.2532	21.7292	31.3098	87.7152	8.6402	1.1213
	30	13.9064	118.1227	23.0352	82.2697	91.6159	8.3264	2.2281
	50	13.9996	127.2730	21.0936	76.5854	87.7983	8.2392	3.6092
Boat	10	13.8982	79.5464	22.0571	38.3080	80.6318	9.1314	1.4433
	30	15.9166	86.8911	22.1387	79.4355	87.3126	9.0925	2.7757
	50	13.7313	89.8386	21.1767	68.6476	87.1549	9.4511	4.3375
House	10	16.1703	83.1156	22.6481	69.3355	84.5845	31.3516	4.3569
	30	22.0690	85.6928	23.2800	84.0503	84.3027	30.7162	8.5521
	50	19.4661	89.4571	22.3112	90.0579	87.8916	30.6753	13.3696
Barbara	10	18.6026	77.1987	21.9312	46.2610	79.1539	8.9904	1.1891
	30	13.2057	85.5030	23.3932	70.8376	85.0245	8.6680	2.2778
	50	12.1874	92.1882	24.0572	84.9135	86.5629	8.3552	3.5315

4. CONCLUSION

Through detailed simulations, this paper compares the median filter and its various alternatives for eliminating or reducing impulse noise from color images. The filters that are ideally suited to noise detection as well as filtering provide fine results in comparison to other approaches as the simulation findings demonstrate. The de-noising filters VMF, FAPGF, TSQSVF, MIVMF, LRDQSF, AWQDF and CAVMFWMF have good PSNR values at low noise levels.

The number of good filters expands to MWMF, MSVMAF, DAMF, BPDF and MDFMF as it comes to visual inspection by SSIM for SAP noise. It concludes that CAVMFWMF provides better NMSE at low noise levels and BPDF is computationally efficient among all the filters for RVIN. The filtering process may be modified in such a way that it reduces the use of blurring methods in the resulting image and deep learning algorithms may be used in conjunction with existing methods to find an effective local and global solution.

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