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MID Filter: An Orientation-Based Nonlinear Filter For Reducing Multiplicative Noise

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Abstract: In this study, an edge-preserving nonlinear filter is proposed to reduce multiplicative noise by using a filter structure based on mathematical morphology. This method is called the minimum index of dispersion (MID) filter. MID is an improved and extended version of MCV (minimum coefficient of variation) and MLV (mean least variance) filters. Different from these filters, this paper proposes an extra-layer for the value-and-criterion function in which orientation information is employed in addition to the intensity information. Furthermore, the selection function is re-modeled by performing low-pass filtering (mean filtering) to reduce multiplicative noise. MID outputs are benchmarked with the outputs of MCV and MLV filters in terms of structural similarity index (SSIM), peak signal-to-noise ratio (PSNR), mean squared error (MSE), standard deviation, and contrast value metrics. Additionally, *F* Score, which is a hybrid metric that is the combination of all five of those metrics, is presented in order to evaluate all the filters. Experimental results and extensive benchmarking studies show that the proposed method achieves promising results better than conventional MCV and MLV filters in terms of robustness in both edge preservation and noise removal. Noise filter methods normally cannot give better results in noise removal and edge-preserving at the same time. However, this study proves a great contribution that MID filter produces better results in both noise cleaning and edge preservation.

Keywords: non-linear filters; MCV and MLV filters; de-noising; noise removal; edge preserving

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1. Introduction

Edge-preserving smoothing is an image processing method that smooths away textures while preserving sharp edges. Most smoothing methods are generally linear low-pass filters that effectively reduce noise at the same time wipe out edges. Since the edges might concern important image information, they have to be protected in smoothing. Non-linear filters are employed for this purpose; however, most of these techniques focus on the problem of reducing additive noise from images, since it is by far the most popular type of corrupting multiplicative noise.

In the literature, there is various research on edge-preserving noise reduction algorithms. Chinrungrueng et al. have presented a study based on edge-preserving noise reduction on ultrasound images. They have introduced a modified 2D weighted Savitzky Golay filter based on the least-squares fitting in a polynomial function to image intensities [1]. Petryniak has described a dynamic image filter using both linear and non-linear image smoothing, based on the Gaussian function. Their filter removes noises in the graphic while preserving information on edges [2]. Yuan and Wang have suggested an edge-preserving and signal-preserving noise removing method based on a Bayesian framework. This filter reduces the number of noises and also adaptively protects edges on signals [3]. Hofheinz et al. have introduced a novel study, which is suitable for bilateral filtering for noise reduction and edge-preserving in the PET image dataset. Bilateral filtering exhibits a successful increase in the smoothing of the PET images while preserving spatial resolution at edges in order to maintain the quantitative accuracy and obtain an acceptable signal-to-noise ratio (SNR) [4]. Pal et al. have presented a survey of benchmark edge-preserving smoothing methods, presented in the literature for computational photography. In their study, they have discussed various effects of the edge-preserving filters also within their optimized modifications and extensions according to their mathematical analysis [5]. Wang et al. have presented a study about a smoothing method with edge preservation for single-image de-hazing (removing haze from image). A novel variational model (VM) that optimizes the transmission in the dark channel has been proposed. This model has an effective linear time complexity in performing transmissions [6]. Storath et al. have introduced a reconstruction framework of edge-preserving and noise reducing for emerging medical imaging, magnetic particle imaging (MPI). Tikhonov regularization, a basic image reconstruction method, is used for MPIs to handle efficiently because of the high temporal resolution of 3D volumes. In their study, they improved an efficient noise removing and edge-preserving reconstruction technique for MPI, giving higher quality in reconstruction for the prototypical medical application of angioplasty [7]. A book chapter for edge-preserving smoothing filters has been written by Burger and Burge. In this detailed and extended study, they have presented noise reduction methods, adaptive smoothing filters for both color and grayscale images. They have especially stressed three conventional types of edge-preserving filters based on different strategies. These are the Kuwahara-type filters, the bilateral filters, and the anisotropic diffusion filters [8]. Additionally, Muhammad et al. have proposed a Bayesian method in which there is a hybrid filtering framework for images having more noises with an unknown variance. The framework, including an automatic parameter selection mechanism, removes noises by enabling an appropriate smoothing and feasible sharpening [9]. In another study, proposed by González-Hidalgo et al., a salt and pepper noise removal system is implemented by a special filter based on a fuzzy mathematical morphology [10]. Luengo et al. have studied noise removal differently by using a supervised learning approach. Specifically, their filter, named CNC-NOS (class noise cleaner with noise scoring), is designed on a noise scoring basis by using ensemble classifiers [11]. A noise-cleaning method for colorful images has been introduced by Pérez-Benito et al. A graph structure is constructed for each of the image pixels in the image by considering some constraints and criterions in order to characterize the pixels as the link cardinality of their connected components [12]. Tang et al. have prepared a detailed study of a smoothing method for edge-aware image manipulations by using a minimization formula of a convex objective function in order to regularize edge and texture pixels in the image [13]. Furthermore, Huang et al. have proposed a technique using an NP-hard method, rank minimization with matrix ranks for regularization in order to remove white Gaussian additive and Gamma multiplicative noises in an image [14].

Apart from those mentioned above, non-linear MCV (minimum coefficient of variation) and MLV (mean least variance) filters are proposed by Schulze et. al. [15] in which multiplicative noise is reduced while preserving the edge contours by employing sliding windows around the central pixel and selecting the pixel that has the minimum amount of coefficient of variation (MCV) and variance (MLV) in terms of intensity within its surrounding window to be low-pass filtered. By this approach, the varying contours, edge lines, and textures are preserved while multiplicative noise is reduced.

In this paper, an extended version of MCV and MLV filters are proposed by modifying its value, criterion, and selection functions to be better than MCV and MLV filters in terms of robustness in noise reduction and edge preservation.

This paper has five sections. There is an introduction with a literature review related to this proposed method in the first section above. Explanations and details of the suggested technique are placed in the second chapter. There are validations of experimental results using statistical metrics and discussion in the third section. Availability of the study is demonstrated in the fourth section. In the last summary section, future work is presented and the contributions are summarized.

2. Methods

In the literature, MCV and MLV filters are well-known filters, which eliminate noises in an image while preserving edges. All these methods similarly use a certain kernel (mask) size, which represents the size and shape of the neighborhood to be sampled while computing the corresponding value. The kernel is a $q \times q$ square matrix where q is a small odd number, generally 3, 5, or 7.

2.1. MCV and MLV Filters

The MCV and MLV filters are edge-preserving noise removing filters based on the concepts of mathematical morphology [16]. They are value-and-criterion filters that are aimed to filter an image only over regions that are generally homogeneous, have low contrast and contain less amount of edges or textures [16]. The difference between MCV and MLV filters is that MCV filter uses the coefficient of variation as the criterion function whereas MLV employs the variance to perform better on multiplicative noise [16].

The idea is basically sliding windows around each central pixel and finding the sub-window, which has the minimum criterion function output, and apply the value function (mean value) of the window belonging to the central pixel [17]. The coefficient of variation over a sliding kernel is calculated by the ratio of the standard deviation to the mean over the sliding kernel. If the image is uniform within the kernel, the variation coefficient becomes very low [17].

On the other hand, if the image has high amount of edge and texture within the kernel, both the coefficient of variation and the standard deviation will return high values [18]. The selection function of MCV and MLV filters is designed as the minimum so that the filtering operation can completely be done over the kernel, which has the smallest output of the criterion function [18]. In other words, the noise smoothing function only acts over these kernels with the smallest coefficient of variation for MCV filter or the variance for the MLV filter [18].

As the value function, mean value is employed over the regions that have the minimum amount of criterion function: The coefficient of variation for the MCV and variance for the MLV filters [18]. The filter structure and detailed explanation of filter design are explained in Section 2.2 within the proposed method.

2.2. Proposed Method: Minimum Index of Dispersion (MID) Filter

The MID filter uses the same morphological structure with MCV and MLV filters to direct low-pass filtering operation to only execute over regions decided to be most nearly constant by calculating the index of dispersion as the criterion function. As previously explained in Section 2.1, MCV and MLV filters employ the coefficient of variation and variance as the criterion function, MID filter employs the index of dispersion as the criterion function. The index of dispersion is the ratio of the variance of a random process to its mean and defined as in Equation (1).

$$D = \begin{cases} \frac{\sigma^2}{\mu} \; if \; \mu \neq 0 \\ 0 \; otherwise \end{cases} \tag{1}$$

where σ is the standard deviation and μ is the mean value of given elements of a set. For an image that is corrupted only by stationary multiplicative noise, the index of dispersion in terms of intensity and orientation in theory is constant at every point. Estimates of the index of dispersion show whether a region is nearly constant under the multiplicative noise or it includes important features. Regions that contain edges or other features generate higher estimates of the index of dispersion in terms of intensity and orientation than areas that are approximately constant. Value, criterion, and selection functions are defined as follows:

$$\omega(x) = \varphi\{f(x); N\} \tag{2}$$

$$\gamma(x) = \delta\{f(x); N\} \tag{3}$$

$$\varphi(x) = \omega(\{x' : x' \in N'_x;\ \gamma(x') = \beta\{\gamma(x); N'\}\}) \quad (4)$$

where ω is the value function, γ is the criterion function, and φ is the selection function. Additionally, $f(x)$ denotes the intensity function that gets the intensity values of each pixel in each window that has N number of elements (pixels) within the window. β is another value function that gets the value of intensity with the minimum index of dispersion. x' denotes the pixels within each sub-window around the central pixel of x and N' is the number of pixels in each sub-window. This filter structure can be described as having a set of sub-windows within an overall filter window. The value-and-criterion filter operation at a point is equivalent to examining each sub-window within the overall window centered at that point and finding which sub-window has the output of optimal criterion function as described by the selection function. Then, the value function output over this sub-window becomes the final filter output for the current point. Value functions are interpreted in Equations (5) and (6) as follows:

$$\omega(x) = \frac{1}{|N|} \sum_{y\, \in\, N_x} f(y) \quad (5)$$

$$\theta(x) = \frac{1}{|N|} \sum_{y\, \in\, N_x} g(y) \quad (6)$$

where ω represents the mean value of intensity and θ denotes the mean value of orientation. As the second metric, in addition to intensity value, normalized gradient orientation values are employed within their magnitudes defined as in Equation (7).

$$g(x) = \arctan\left(\frac{G_y}{G_x}\right) \times \sqrt{{G_y}^2 + {G_x}^2} \quad (7)$$

where G_y is the vertical gradient vector's normalized magnitude and G_x is the horizontal one. A 3×3 Sobel operator is employed to find the gradient vectors for each pixel of the input image. The regions that have a chaotic distribution of orientations are also defined as noise since regular patterns of orientation distributions land on the regions without noise. Therefore, orientation dispersion is also employed as the second metric in the proposed filter. Less dispersion in the orientation will have more impact on the intensity distribution. Thus, the criterion function is re-modeled as follows:

$$\gamma(x) = \frac{\frac{1}{|N|} \sum_{y\, \in\, N_x} [f(y) - \omega(x)]^2}{\omega(x)} \times \left(1 - \frac{\frac{1}{|N|} \sum_{y\, \in\, N_x} [g(y) - \theta(x)]^2}{\theta(x)}\right) \quad (8)$$

Elimination of multiplicative noise from images is commonly more difficult than additive noise since the noise intensity varies with the signal intensity. In order to avoid this, selection function is re-modeled by adding an alpha parameter, which adds a low-pass value to the output of selection function. Alpha is a normalized parameter and it transforms the filter into a fully mean filter when it is set to 1. The proposed selection function is defined as follows:

$$\forall(x) = \omega(\{ x' : x' \in N'_x;\ \gamma(x') = \min[\gamma(y);\ y \in N'_x]\}) \quad (9)$$

$$MID\{f(x); N\} = \forall(x) \times (1 - \alpha) + \omega(x) \times \alpha \quad (10)$$

The sample mean is accepted as the value function for the MID filter. Thus, the MID filter uses the sample mean for a value function, the index of dispersion as a criterion function, and the minimum as a selection function. This value-and-criterion filter is particularly designed to remove multiplicative noise. Theoretically, index of dispersion in the images corrupted by noises is minimum in structuring elements where there is the constant signal. The MID filter in images both preserves sharp edges between flat areas and enhances the edges, which are not perfect step edges.

This study especially indicates a structural design of a special filter, which is the extended version of MCV, and MLV architectures. This filtering method is an edge-preserving noise reduction technique designed for reducing multiplicative noise by using the structure of the value-and-criterion filter. The theoretical mechanism of this method stands on the well-known fundamentals of geometrical properties. The advantage of this method is that it successfully preserves edges in the regions corrupted by the multiplicative noise and enhances them while preserving the morphological structures of the image.

3. Experimental Results and Analysis

Mainly, all of the experiments have been performed on the Computational and Subjective Image Quality (CSIQ) benchmark dataset [19] by using a normal computer. MID filtering is implemented using Processing in Java and testing is performed in the MATLAB environment.

3.1. CSIQ Image Quality Database Specifications

The CSIQ database is a popular image quality-benchmark test set in order to evaluate algorithms. The database includes 30 original images at the resolution of 512×512 pixels. The set is distorted using one of six distortions with four to five different distortion levels. CSIQ images have been tested based on linear image displacements on four calibrated LCD screens placed side by side with equal viewing distance. This database contains 5000 subjective evaluations from 35 different observers and the assessment are presented in the form of difference mean opinion scores (DMOS) in which a larger one indicates greater visual impairments compared to the corresponding reference image.

3.2. Performance Measurement Criterions

De-noising a picture requires a successful method providing that edges are to be preserved. In order to evaluate the performances of the methods, some quality metrics are preferred. Evaluation of de-noising quality is performed five fundamental metrics. These are mean squared error (MSE), peak signal-to-noise ratio (PSNR), the structural similarity index (SSIM), contrast, and standard deviation [20]. Additionally, *F* Score, which is an original hybrid metric for comparison, is proposed in this study by using the combinations of the basic measurements.

3.2.1. Mean Squared Error (MSE) and Peak Signal-to-Noise Ratio (PSNR)

Both MSE and PSNR are used to evaluate the performance for image manipulation algorithms. They are similar to each other and derived from signal processing. Implementation and calculation are straightforward, but the results are not always considered reliable as they show aspects in various situations. Nevertheless, they have a great role in the performance evaluation domain.

The MSE between the two signals is described as seen in Equation (11).

$$MSE = \frac{1}{N \times M} \sum_{i=0}^{N-1} \sum_{j=0}^{M-1} [X(i,j) - Y(i,\ j)]^2 \tag{11}$$

where X and Y are two arrays of size $N \times M$. The closer Y is to X, the smaller MSE will be. When the MSE is equal to zero, apparently, the maximum similarity is achieved.

The PSNR (in dB) accordingly is defined as follows:

$$PSNR = 10 \log_{10} \frac{L^2}{MSE} \tag{12}$$

In Equation (12) above, L is the maximum fluctuation in the data type of the input image. For instance, if the input image has a double-precision floating-point data type, then L is defined as 1. Similarly, if the input image has an 8-bit unsigned integer data type, L is defined as 255. Logarithm transforms the ratio into a decibel (dB) scale, which is a common scale operation in signal processing. PSNR in decibels units calculates the PSNR between original and filtered images. The lower the PSNR value, the worse the quality of de-noised image. MSE and PSNR are the two-error measurement metrics used to compare the image de-noising quality.

MSE shows the cumulative squared error between filtered and original images. PSNR displays the measure of the peak error. In a little while, the higher the MSE value, the higher the error. If there are two identical images (in the absence of artificial noise), the MSE value becomes 0 and the PSNR value becomes infinite [21].

3.2.2. The Structural Similarity Index Measurement (SSIM)

The SSIM measurement is a common and well-known quality criterion to determine the similarity between two images. The SSIM index gives a similarity percentage in the interval of [0, 1].

This measurement style compares two images in the same size, the de-noised picture, and the original picture. The original picture is assumed as it has perfect quality. The de-noised one is for test and the original is for verification. SSIM index is defined as follows:

$$SSIM(x,y) = \frac{\left(2\mu_x\mu_y + C_1\right)\left(2\sigma_{xy} + C_2\right)}{\left(\mu_x + \mu_y + C_1\right)\left(\sigma_x + \sigma_y + C_2\right)} \tag{13}$$

where x and y are the two different images with μ_x and μ_y mean values of intensity and standard deviations of σ_x and σ_y with contrast values C_1 and C_2 for the two images separately. When comparing two images, MSE does not indicate highly perceived similarity while implementation is simple. Structural similarity is aimed at addressing this hardship.

3.2.3. Contrast

Contrast of an image might be simply explained as the difference between the minimum and maximum pixel intensity. Shortly, it is the difference in color or luminance for a group of objects. In this project, edge-based contrast measure (EBCM) for image quality evaluation is selected as a performance metric [22]. This metric is based on the fact that an enhanced image normally has more edge pixels than the original image. The EBCM metric calculates the intensity of edge pixels in small windows of the image.

3.2.4. Standard Deviation

The standard deviation of the pixel intensity values is used to quantify the amount of variation or dispersion of a grayscale image. It is calculated by Equation (14).

$$\sigma = \sqrt{\frac{1}{N \times M}\sum_{i=0}^{N-1}\sum_{j=0}^{M-1}\left(x_{ij} - \mu\right)^2} \tag{14}$$

where σ is the standard deviation of matrix elements. N and M are the vertical and horizontal sizes of the image. x_{ij} is the pixel of the ith line and jth column. μ is the arithmetic mean. A low standard deviation value displays that the pixels tend to be close to the mean of the image, while a high value shows that the pixels are spread out over a wider range of values.

3.2.5. A Hybrid Assessment Metric: F Score

Handling each of the metrics separately in image quality assessment might be difficult. A hybrid approach is proposed to evaluate each of the filter methods as shown in Equation (15).

$$F \text{ Score} = 100 \times \frac{PSNR \times SSIM \times Contrast}{Std.Dev \times MSE} \tag{15}$$

An optimal edge-preserving and noise-reducing filter should increase the PSNR, SSIM, and contrast values while reducing the standard deviation and MSE values. Therefore, a compact formula of *F* is generated in order to benchmark the filters. Higher values of PSNR, SSIM, and Contrast values indicate that there is a successful smoothing operation.

In contrast, higher values of standard deviation and MSE shows poor smoothing results. In other words, PSNR, SSIM, and contrast have a positive effect on image quality, whereas the others have a negative impact.

In the experiments, *F* scores result in very tiny values, even very close to zero. Hence, the *F* score results are multiplied by a constant value of 100 so as to optimize the outputs. A regularly higher *F* score rate indicates the successful filtering performance.

3.3. Comparison Steps of Experimental Outputs

In the experimental, the overall procedural steps are illustrated in Figure 1.

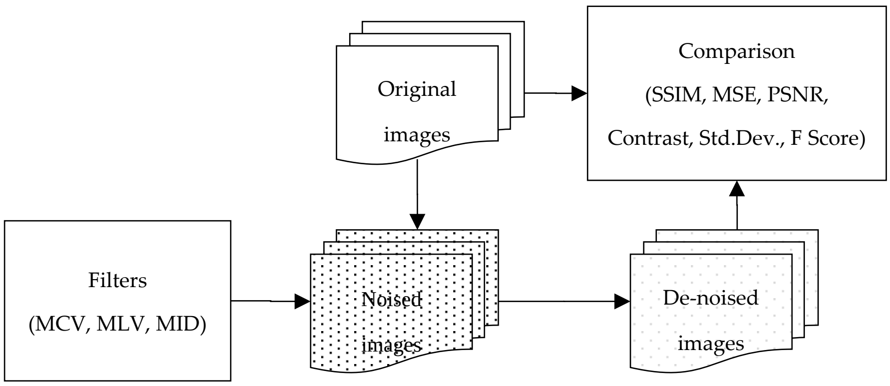


Figure 1. Procedural steps for overall comparisons.

Firstly, the original images are synthetically noised with the multiplicative noise option, using Equation (16) for an image *I*.

$$J = I + n \times I \tag{16}$$

where n is evenly distributed random noise with mean 0 and variance v. The default value for v is set to 0.04. Then, each of the filtering methods (MCV, MLV, and MID) is employed to de-noise the noised images. In other words, the noised images are filtered by the 3 filtering methods in order to clean the noises. Each method produces individual outputs. Lastly, the outputs are compared with the original images using the metrics of PSNR, MSE, SSIM, contrast, standard deviation, and *F* score.

As the experimental setup, artificial multiplicative noise is added to the 30 CSIQ images in order to quantify the performance of filters in terms of robustness to noise and edge preservation. Filtered images are compared with the original images with respect to five main metrics: PSNR, SSIM, MSE, standard deviation, and contrast. Table 1 illustrates an original image and a multiplicative noise added image.

In Table 1, the first image is the original gray-scale form of the CSIQ "1600.png" image, which has a contrast value of 74.19 and standard deviation of 66.21. The second one is the multiplicative noise-added gray-scale form of the CSIQ "1600.png" image, which has a contrast value of 67.25 and standard deviation of 75.83. After adding noise, standard deviation is increased and contrast is decreased since the noise factor increases the deviation from the mean while it wipes out the edges, which lowers the contrast accordingly.

Table 1. Original and artificially noised "1600.png" image (the v variance parameter for multiplicative noise is set to 0.04).

Original Picture	Noisy Picture
	
Std.Dev.: 66.21 Contrast: 74.19	Std.Dev.: 75.83 Contrast: 67.25

3.4. Numerical Outputs and Discussion

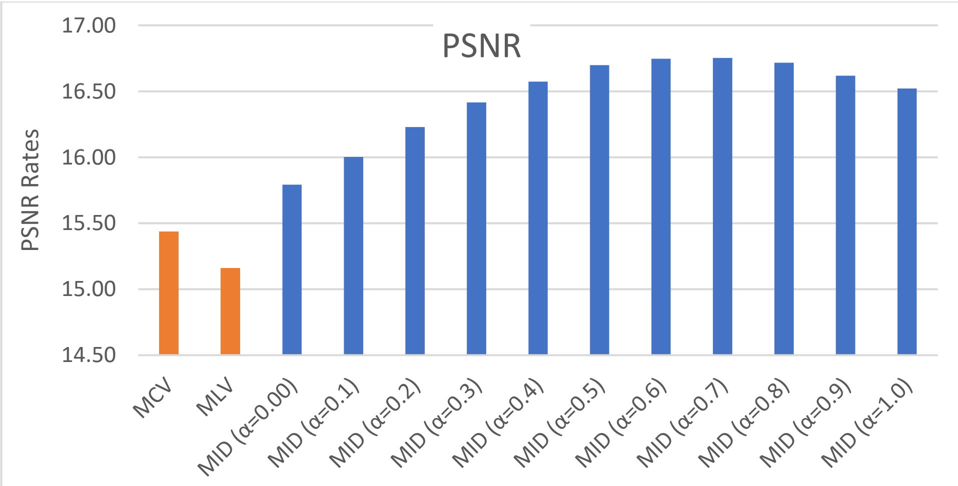
As the experimental setup, pictures are compared with the original gray-scale pictures so that selected metrics can be examined. For this purpose, pictures filtered out by MCV, MLV, and MID filters are compared with respect to selected six metrics: PSNR, MSE, SSIM, standard deviation, contrast, and *F* Score. In the performance assessments, it is observed that PSNR and SSIM values increase while MSE decreases. Standard deviation decreases if the amount of noise is decreased. Also, the contrast is increased if the edge contours are enhanced. *F* Score demonstrates the overall success rate. Table 2 demonstrates a set of sample experimental results for the selected gray-scale form of the "1600.png" image as follows.

Table 2. Sample experimental results for a gray-scale picture taken from filters with 5 × 5 kernel size.

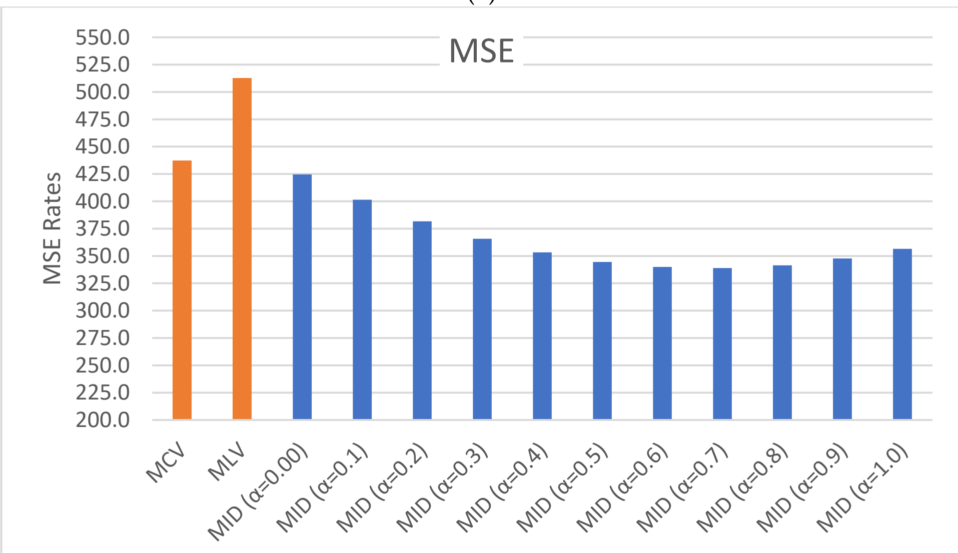
MCV Filter	MLV Filter	MID Filter (α = 0.00)
		
PSNR: 14.16 MSE: 527.36 SSIM: 0.54 Contrast: 65.51 Std.Dev.: 62.58 F Score: 1.45	PSNR: 14.24 MSE: 487.06 SSIM: 0.55 Contrast: 63.36 Std.Dev.: 64.89 F Score: 1.55	PSNR: 14.56 MSE: 466.09 SSIM: 0.56 Contrast: 64.48 Std.Dev.: 63.89 F Score: 1.74

According to the experimental outputs shown in Table 2, the highest *F* Score is obtained in the MID Filter with the parameter (alpha = 0.0) when the comparison is performed among all filters. It indicates that the highest amount of noise reduction occurs with the MID Filter.

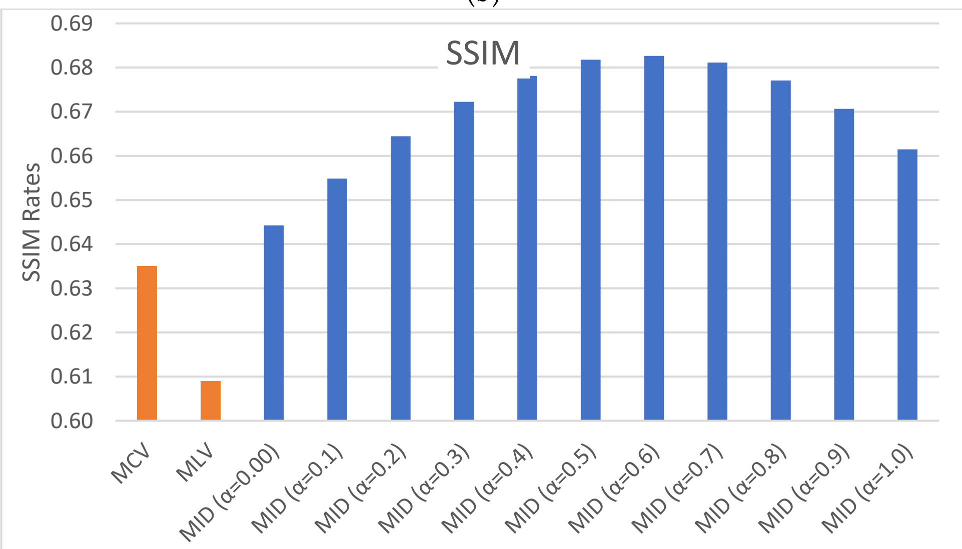
Figure 2 demonstrates the MSE, PSNR, SSIM, contrast, standard deviation, and *F* score bar charts of each filter as follows:



(**a**)

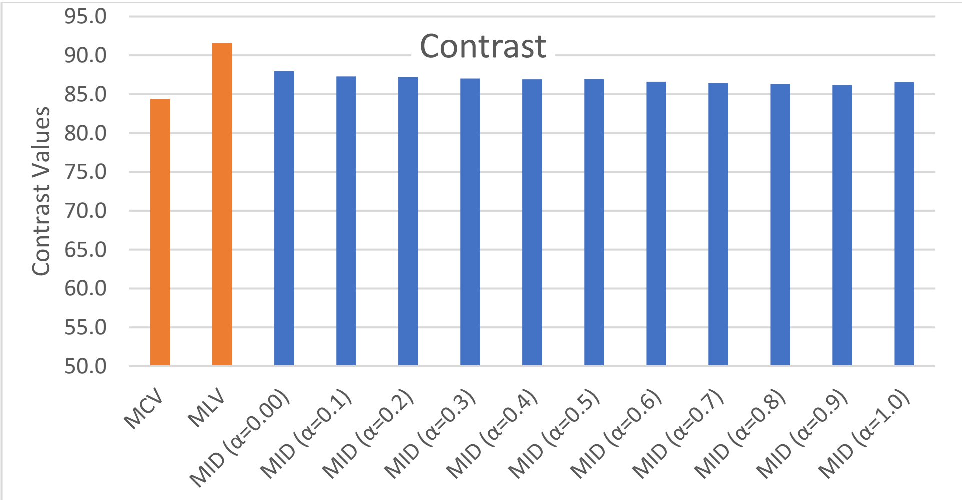


(**b**)

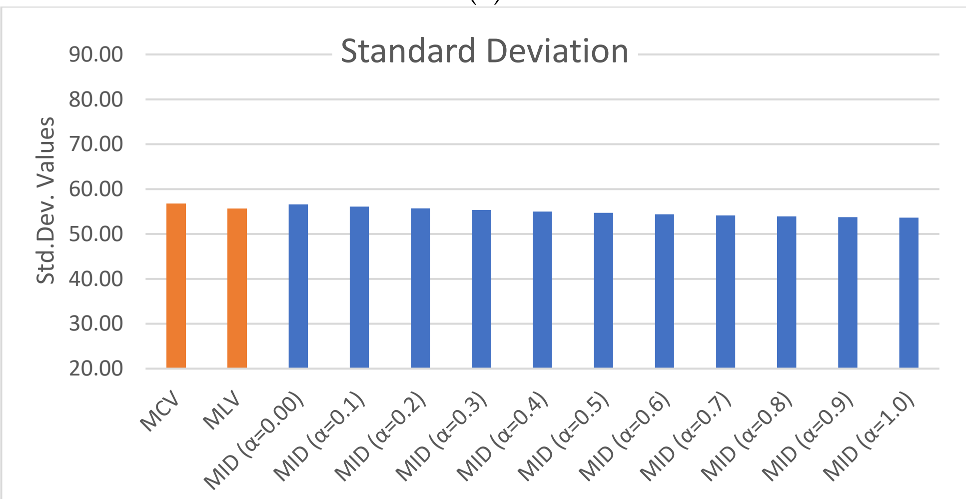


(**c**)

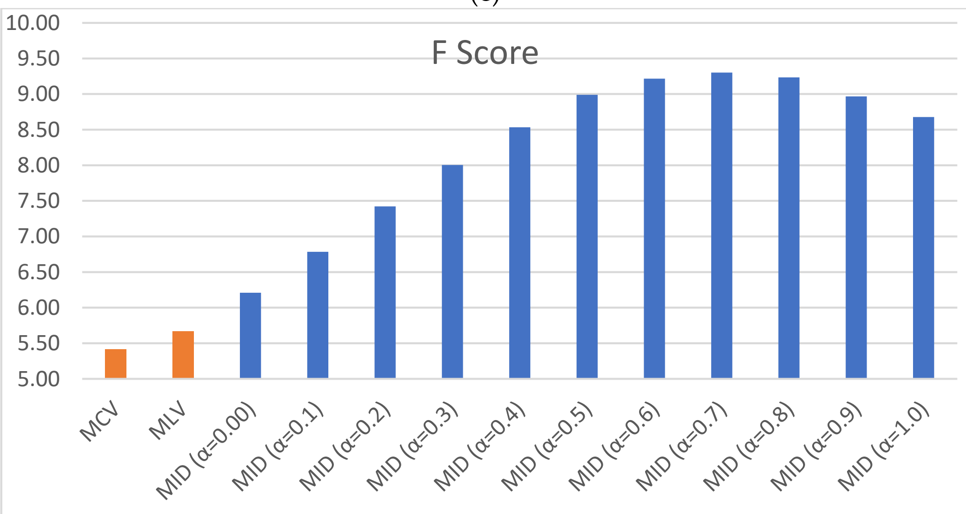
Figure 2. *Cont.*



(**d**)



(**e**)



(**f**)

Figure 2. Average peak signal-to-noise ratio (PSNR) rates in decibel (dB) (**a**), average mean squared error (MSE) values (**b**), average structural similarity index (SSIM) rates (**c**), average contrast values (**d**), average standard deviations (**e**), and average *F* scores (**f**) for the gray-scale computational and subjective image quality (CSIQ) dataset.

According to Figure 2, when MCV, MLV, and MID filters are compared in terms of PSNR, MSE, and SSIM, MID filter leads in the group. It has the highest rate of SSIM, and the lowest amount of MSE and the highest rate of PSNR.

Furthermore, the success rate of MID filter will increase when the alpha parameter is increased. However, too much increment in alpha will ruin the structural similarity and reduce the contrast; therefore, the optimal value of the alpha should be determined which will balance the ratio between SSIM and contrast. According to experimental tests, optimal alpha value, which yields the best results, is discovered as 0.30.

Observations through experiments are performed with respect to six metrics: PSNR, MSE, SSIM, Standard Deviation, Contrast, and *F* Score. The most determinant metrics appear as PSNR and SSIM, which indicates the percentage of noise reduction and similarity with the original pictures. Table 3 indicates the overall results with alternative values of alpha.

Table 3. Total average results of filtering experiments when the kernel size is set to 5.

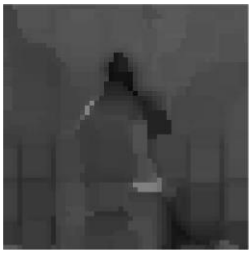
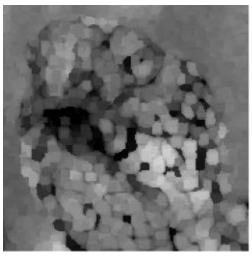
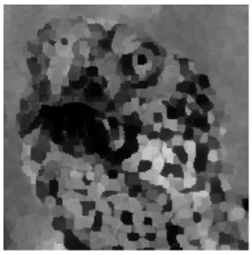
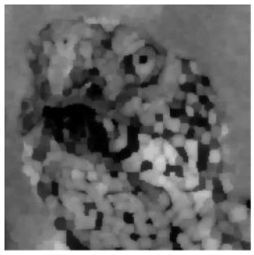
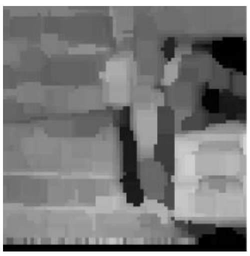
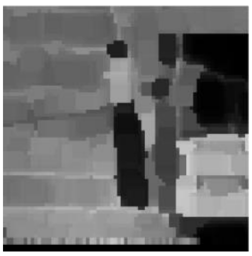
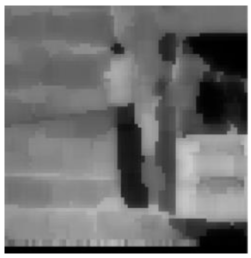
	PSNR	MSE	SSIM	Std. Dev.	Contrast	*F* Score
MCV	15.44	437.0	0.635	56.81	84.4	5.42
MLV	15.16	512.6	0.609	55.71	91.6	5.67
MID (α = 0.0)	15.79	424.6	0.644	56.60	88.0	6.21
MID (α = 0.1)	16.00	401.5	0.655	56.12	87.3	6.78
MID (α = 0.2)	16.23	381.7	0.664	55.72	87.2	7.42
MID (α = 0.3)	16.42	365.7	0.672	55.34	87.0	8.00
MID (α = 0.4)	16.57	353.4	0.678	55.00	86.9	8.53
MID (α = 0.5)	16.70	344.5	0.682	54.70	86.9	8.99
MID (α = 0.6)	16.75	339.9	0.683	54.40	86.6	9.22
MID (α = 0.7)	16.75	338.9	0.681	54.14	86.4	9.30
MID (α = 0.8)	16.72	341.4	0.677	53.94	86.3	9.23
MID (α = 0.9)	16.62	347.8	0.671	53.75	86.2	8.97
MID (α = 1.0)	16.52	356.6	0.661	53.63	86.5	8.68

In Table 3, the average PSNR value with MID filter is obtained as 16.42 while MCV and MLV filters attain 15.16 and 15.44, respectively. This proves that the MID filter is superior to the MCV and MLV filters in terms of robustness to noise and the SSIM value is calculated as 0.672 while the MCV and MLV filters reach 0.609 and 0.635, respectively. This also proves that the MID filter is better than the MCV and MLV filters in terms of similarity with the original pictures, which means MID filter cleans the noise while preserving the structural similarity with the original pictures. Mean squared error (MSE) is also observed as lower than the MCV and MLV filters where the MSE of MCV is observed as 512.6 and MSE of MLV is observed as 437.0, which is much higher than the MSE of the MID filter obtained as 365.7 through the experiments. This also proves that the MID filter's outputs are much more similar to the original pictures and cleans the noise better than the MCV and MLV filters. As an overall evaluation, the MID filter is better than the MCV and MLV filters in terms of robustness to noise while preserving the edges.

Additionally, the rows of Table 4 contain some cropped sections from original and filtered images of CSIQ "1600.png", "family.png", "turtle.png", and "trolley.png", respectively. These gray-scale pictures are from the original picture, MCV, MLV, and MID filters using a kernel size of 5×5 matrix. Table 4 demonstrates the visual performances of filters on edge preservation.

According to Table 4, in the first image in the first row, there are iron fences behind the people. The fence is a good representation (sample) of edges. As it is seen, the fence in MCV is thinner than in MLV. Edge contours of the fence are not well preserved by both MCV and MLV filters, whereby MCV makes edges thinner and MLV makes thicker than normal. Furthermore, in the first and second images in the first and second rows, the heads of people in MCV almost disappear since the mean method shrinks the edges. On the other hand, the heads of people in MLV are oversized since the method expands the edges [23]. However, the heads of people in the MID filtered image looks neither oversized nor shrunken since the proposed method employs orientation information that optimizes the size of contours. In the third row, the head of the turtle loses its texture when MCV is applied, and contours become thicker when MLV is applied. However, both edge contours and textures become normal when the MID filter is applied. Additionally, in the fourth row, humans on the trolley almost disappear when MCV is applied and contours become extremely thicker when MLV is applied. On the other hand, both contours and texture look normal when the MID filter is executed.

Table 4. Some small cropped image sections from the outputs of filters.

Original Section	**MCV**	**MLV**	**MID**
			
1600.png	PSNR: 10.60 SSIM: 0.570	PSNR: 10.65 SSIM: 0.638	PSNR: 11.49 SSIM: 0.630
			
family.png	PSNR: 9.44 SSIM: 0.430	PSNR: 11.29 SSIM: 0.600	PSNR: 11.82 SSIM: 0.617
			
turtle.png	PSNR: 11.37 SSIM: 0.531	PSNR: 13.03 SSIM: 0.640	PSNR: 13.82 SSIM: 0.670
			
trolley.png	PSNR: 10.78 SSIM: 0.507	PSNR: 11.37 SSIM: 0.582	PSNR: 12.24 SSIM: 0.605

As it is widely accepted, preserving edges is a great issue in noise reduction operations. The primary orientation of this study stands on two main principles, edge preservation and noise reduction. Measuring the quality of edge preservation might be performed by the SSIM index. The performance of noise-cleaning might be also assessed by the *F* score.

As it is seen in the experimental results above, the MID filter gives better results than the MCV and MLV filters starting from when the alpha is set to 0.30 according to SSIM index. Since the SSIM index indicates structural similarity of objects in the pictures, it also gives a sign about the rate of edge preservation. The more alpha is increased, the more the filter behaves like a mean filter, which ruins the edge preservation. Therefore, a minimum optimal value of alpha is necessary to get better results in terms of both edge preservation and noise reduction. For this reason, 0.30 might be determined as the optimum value of alpha. Even though the highest SSIM is gained when the alpha is set to 0.70, the edges partly disappear since MID behaves like a mean filter. As the main purpose of the study is to protect edges from deformations, the alpha parameter should be lessened as much as possible.

As a result, the shape of the objects changes with respect to type of filters. While MCV filters ruin the object boundaries, the MLV filter over-blurs the edge contours, which results in thick borderlines of the objects. However, the MID filter preserves the original contours of objects since the MID filter employs orientation information as the criterion function. This is the most prominent contribution of this study. This improvement can be recognized with the SSIM metric, which indicates the structural similarity of objects within the image pairs. Additionally, *F* score is presented as a novel comparison metric, which separates the filters in terms of edge preservation and robustness to noise.

4. Availability

This presented MID filtering model has been implemented in the Java Processing and tested in MATLAB platforms. For examinations, further studies, and citations, all of the written original codes, benchmark datasets, test images, outputs, and total experimental results including SSIM, MSE, PSNR, contrast, standard deviations, and *F* scores for all cases can be publicly reachable at the website: https://sites.google.com/site/bulutfaruk/study-of-mid-filtering.

5. Conclusions

In this paper, an extended version of MCV (minimum coefficient of variation) and MLV (mean least variance) filters are proposed. The proposed approach is the MID (minimum index of dispersion) filter, which employs orientation information of pixels in order to support value-criterion structure of the MCV and MLV filters. The dispersion of orientations is employed as the criterion function, which yields better results against multiplicative noise. Moreover, the value function is modified by adding an alpha parameter, which acts as low-pass filtering by the amount of alpha. Experimental results show that the proposed approach produces better results than MCV and MLV filters against multiplicative noise and eliminates the weaknesses of MCV and MLV filters. As the metric for measuring the robustness to noise, SSIM (structural similarity index), MSE (mean squared error), PSNR (peak signal-to-noise ratio), standard deviation, and contrast values are employed. Additionally, *F* Score, a hybrid metric that is the combination of five metrics is introduced in order to compare the filters. Benchmarking study indicates the MID filter is superior to the MCV and MLV filters. By the increment of the alpha parameter, the noise is blurred but the contrast is decreased, which acts by blurring the edges as well. Therefore, a balanced alpha parameter value is necessary, which will enhance the edges and at the same time blur the multiplicative noise. As the optimal value of the alpha parameter, 0.30 is determined according to experimental tests. This study might be an innovative guide for those who are interested in MCV and MLV filters and able to output different studies on the topic in the future.

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