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DESIGN AND IMPLEMENTATION OF THE BLOCK MATCHING HYBRID MEDIAN FILTER FOR NOISE REMOVAL IN COLOR IMAGES

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Abstract. *In this paper we propose a Block Matching Hybrid Median Filter (BMHMF) algorithm to improve the operation of the Decision Based Median Filter. The BMHMF algorithm combines three different techniques, Adaptive Median Filter (AMF), Modified Vector Median Filter (MVMF), and Block Matching (BM) for impulse noise filtering and correction of artificial color generated in an image. The scalar median filter is used to separate the Red, Green, and Blue (RGB) components in parallel. This process detects the smallest dissimilarity measure of impulse noise in each component of the color image. However, it generates color artifacts in the image, which causes blurring and sharpness. The MVMF corrects, smoothens and removes the color artifacts in that image, which completely restores the color quality. The primary task of the block matching technique is to recover the dead edge pixels and the corrupted image detail. The BMHMF is implemented in MATLAB and applied to several noisy color images to test the performance of the filter. The results of the experimental analysis show that the proposed filter outperforms existing filters in noise (impulse) detection and removal.*

Keywords: Block Matching, Impulse noise, Vector Median Filter, Adaptive Median Filter, Decision Based Median Filter, RGB components, Edge pixel, Fine image details

1. **Introduction.** Color images have been used in diverse areas of application such as context-based image retrieval centers, medical image analysis centers, biometrics centers, criminal division sections, remote sensing sectors, watermarking sections and visual quality inspection departments. These images are preferred to the greyscale counterpart because they contain much information that is very useful in image analysis (object identification and extraction based on color) [1-3]. The need for preprocessing of images is to make further processing easier. However, noise makes an image lose its quality, which requires further image processing and intensive computional analysis.

For faster and easier analysis, images must be bright, clear and identifiable. Usually images are corrupted by impulse noise, which degrades their quality. This impulse noise, such as salt and pepper, is a random variation of brightness that appears in the image to distort it. The noise in color images mostly occurs through data transmission, faulty sensors or such electrical disturbance as lighting [2,4]. Thus, impulse noise creates loss in the perceptual quality of the image and also makes high-level processing computationally intensive.

For high-level-signal processing such as segmentation, clustering and classification to be successful, the noise in the image must first be removed (preprocessed) to aid further processing. However, to enhance signal processing, the image must first be preprocessed [3]. A lot of filters have been suggested for the removal or reduction of impulse noise from images (greyscale and color). For example, the nonlinear ordered statistics filters have proven to be more successful in impulse noise removal. These filters also perform well in restoring image details and edges [3,5,6].

The class of ordered statistics filters are categorized into scalar and vector filters [7]. The scalar median filter [7] and all its adaptive counterparts belong to the family of the nonlinear scalar filters. These filters were originally designed for filtering impulse noise from 2D greyscale images. However, they have recently been applied to color images due to their performance. Though the class of scalar filters performs very well in the suppression of noise in color images, they introduce color artifacts into the image. Moreover, the Vector Marginal Median Filter (VMMF) is a recently improved scalar median filter proposed to enhance the performance of the family of scalar median filters in noise removal from color images [8]. Yet, the VMMF partially solves the problem in the scalar median filters; the problem of generating artificial colors remains unsolved. This problem remains because the scalar filters work on color images channel by channel and independently to obtain the desired output.

Another class of filters is the Vector Median Filter (VMF) [9], which develops the color image pixels as a vector takes account of the inter-channel correlation of pixels in the image. This concept is expected to overcome the artificial color generation of the scalar filter family. To the family of vector filters that are based on the VMF belong the Basic Vector Directional Filter (BVDF) [10], Distance-Directional Filter (DDF) [11], and Generalized Vector Directional Filter (GVDF) [12]. Because these filters have roots in the theory of robust statistics [6,9,13], they treat each pixel of the color image as a vector. The filters in this family perform quite robustly with regard to impulse noise without introducing color artifacts but allowing for the inter-components correlation among the RGB components. However, this class of filters has its limitation. Such filters are applied uniformly to an image, even to regions of the image where there is no noise. This procedure introduces some distortion into the image. Thus, the noise reduction capabilities of this class of filters are low due to the distortion. In addition, the vector median filter family produces bad results for regions

where each vector population has one noisy component. In this case, the vector filter always chooses a noisy optimal pixel as its vector median because the filter does not adapt to the extremely noisy situation [14].

Research suggests several vector filters, including the Adaptive Vector Filters [8,15], Hybrid Vector Filters [14], Fuzzy Vector Filters [16], and Decision Based Vector Filters [17-19]. The most recent filters are the Fuzzy Vector Filters and the Decision Based Vector Filters. These filters have demonstrated their enormous performance in noise filtering. The Decision Based Median Filter (DBMF) is supposed to solve two fundamental problems: problems encountered when vector filters are uniformly applied to an image and blurring problems encountered by extensions of DBMF [17-19]. The DBMF adopts a technique which makes its window size adjustable and not fixed. This adjustability is important because the computational time of the filter depends heavily on the size of the window. This way, the Decision Based Unsymmetric Trimmed Median Filter (DBUTMF) improves the performance of the DBMF [5,20] while the Modified Decision Based Unsymmetric Trimmed Median Filter (MDBUTMF) further improves the DBUTMF [5,21]. Though MDBUTMF performs well, it has a challenge in detecting noise in one color component if it appears with the smallest dissimilarity measure, which introduces distortions into the image details and edges. Hence, this class of filters has a difficulty in detecting and suppressing noise pixels in a region of a mixture of highly dense impulse noise with bright image pixels and edge pixels [5,20,21].

This work proposes a method to improve the operation of the Decision Based Median Filter and its extensions. The proposed method is designed to detect impulse noise in an individual color component of the image if it appears with the smallest dissimilarity measure. This method is a hybrid that combines three different techniques for noise filtering and correction of artificial color generated in the image. It produces a robust hybrid filter design that is able to filter impulse noise (in regions of a mixture of highly dense impulse noise with bright image pixels and edge pixels) without introducing color artifacts and blurring the image. The results of the experimental analysis show that the proposed filter outperforms the state-of-the-art filters in noise (impulse) detection and removal.

The rest of the paper is organized as follows. A brief introduction of the filtering process is given in Section 2. Section 3 outlines a detailed description of the design processes of the proposed filter. Experimental results and comparisons are provided in Section 4. Finally, conclusions are drawn in Section 5.

2. **Block Matching Hybrid Median Filter Design Mechanism.** This section presents the basic idea of the Block Matching Hybrid Median Filter (BMHMF). The BMHMF can overcome challenges faced by the Decision Based Vector Filter family. The BMHMF combines three modified techniques: the Adaptive Median Filter Technique, the Modified Vector Median Filter Technique and a Block Matching. The BMHMF's operation is categorized into three main phases.

a. The first phase of the BMHMF deals with the application of the Adaptive Median Filter to the RGB components separately (applying the median filter to each color component independently). This process recovers the color image from the impulse noise corruption in each element but introduces some color artifacts in the image causing the image to be blurred and sharp.
b. The second phase applies the Modified Vector Median Filter to the output of the result in the first phase. The color artifacts introduced in the color image is corrected by using the Modified Vector Median Filter to the image.
c. Finally, the block matching process is used to restore the color image completely. The primary task of the block matching technique is to recover the dead or polluted edge pixels as well as recover the corrupted image details. The corrupted edge pixels are detected and corrected by the 3×3 block to block comparison of patches extracted from the corrupted image and the filtered image. This process is very computationally intensive, but it succeeds in correcting the rest of the distortions and color mismatch problems.

Figure 1 gives a clear picture of a detailed framework of the stage in the Block Matching Hybrid Median Filter process.

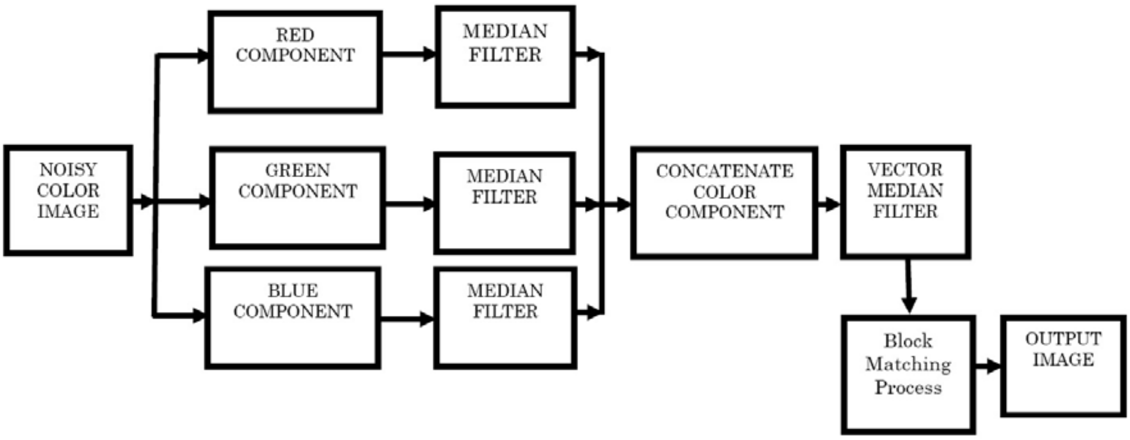

FIGURE 1. Framework of the Hybrid Median Filtering process

3. Phases of the BMHMF Development.

3.1. Phase one: design of the BMHMF. The Adaptive Median Filter (AMF) is chosen for the BMHMF due to its effective performance in impulse noise suppression in 2D greyscale images. Moreover, the AMF addresses the main shortcomings of the standard median filter and also outperforms most of the existing scalar median filters [3,22]. Also, the AMF has a very robust noise detection mechanism that operates by applying a local spatial processing to detect the noisy pixel. It performs the local processing by comparing each pixel in the region to all the surrounding pixels in the defined region. The maximum value (K_{max}), minimum value (K_{min}) and median value (K_{med}) of the window are computed. The differences between the minimum and the median ($R1 = K_{med} - K_{min}$) and the maximum and the median ($R2 = K_{max} - K_{med}$) are computed. The result of this computation is checked at level 1 ($R1 > 0$ AND $R2 < 0$), whether the median value is impulsive or not.

The process continues to the next step of the local preprocessing. If the median is not impulsive, the window is increased by 2 (that is from 3×3 to 5×5), and the initial step is repeated. The succeeding step computes the difference between the minimum value (K_{min}) and the center pixel value (K_{XY}), [$Q1 = K_{XY} - K_{min}$], the maximum value (K_{max}) and the center pixel value (K_{XY}), [$Q2 = K_{XY} - K_{max}$]. This stage is checked at level 2 ($Q1 > 0$ AND $Q2 < 0$), whether the center pixel value is impulsive or not. The center pixel value is replaced with the median ($K_{XY} = K_{med}$), if the condition at level 2 holds; otherwise it is left intact.

The window moves to the next location and continues until it covers the entire image. The dynamic overlapping window is supported with an adjustable local threshold for the processing, which contributes to the effective results obtained by the filter. The noise detection mechanism detects the center pixel as noisy in the second level of the algorithm (Figure 2). If the difference shows that the center pixel deviates from the majority of its neighbors and lies structurally far away from the rest of the surrounding pixels in the chosen region, the noisy pixels would cause distortions in the image and degrade the quality of the image. To suppress the distortion in the image, those noisy pixels must be replaced. The AMF process serves this need because it produces good results when applied to grey scale images, though it introduces some color artifacts when applied to color image. However, it performs well in filtering out a greater percentage of the impulse noise in the color image. So, the BMHMF applies the AMF to each of the color and the computed results of each filter are merged and fed into phase 2.

The median of N scalars x_i, $i = 1, 2, 3, 4, \ldots, N$ can be defined as the x_{med} such that the cummulatve sum of the absolute difference between the median and all its neighbors is less than all the values x_j, $j = 1, 2, \ldots, N$, expressed in Equation (1).

$$\sum_{i=1}^{N} |x_{\text{med}} - x_i| \leq \sum_{i=1}^{N} |x_j - x_i| \tag{1}$$

The following algorithm explains the mode of operation of the Adaptive Median Filter:

Algorithm of the Adaptive Median Filter (AMF)
$\mathrm{K_{med}}$: Computed median value in a window
$\mathrm{K_{min}}$: Computed minimum value in a window
$\mathrm{K_{max}}$: Maximum pixel in the region
W_Size: Chosen window size
W_Size$_{\max}$: Maximum window size
Level 1: $\mathrm{R1} = \mathrm{K_{med}} - \mathrm{K_{min}}$
$\mathrm{R2} = \mathrm{K_{med}} - \mathrm{K_{max}}$
if R1 > 0 AND R2 < 0, go to level 2
Elseif W_Size < W_Size$_{\max}$ increase the W_Size and repeat level 1
Else output $\mathrm{K_{XY}}$
Level 2: $\mathrm{Q1} = \mathrm{K_{XY}} - \mathrm{K_{min}}$
$\mathrm{Q2} = \mathrm{K_{XY}} - \mathrm{K_{max}}$
if Q1 > 0 AND Q2 < 0, output $\mathrm{K_{XY}}$
Else output $\mathrm{K_{med}}$

3.2. **Phase two: design of the BMHMF.** The result of the AMF in phase one is fed into the Modified Vector Median Filtering (MVMF) phase. The MVMF modifies the Vector Median Filter (VMF) [9], which is a nonlinear, local order based processing technique that treats the pixels of the RGB components as vector fields. This process overcomes the artificial color generation problem encountered by the scalar filters as it works on the entire image by applying the moving window technique over the image [15,23,24]. However, at each window location the vector median value is computed within the window, and then the center pixel is replaced with the median value. The VMF uses the reduced ordering technique to sort the vector pixel values in the window. This reduced ordering technique applies the L2-norm for the computing of the relative cumulated distances for sorting the pixels in the window. Thus, the vector pixel with the minimum aggregate distance is selected as the vector median value. However, as the vector median filters have no noise detection method, all the center pixels at every window location are replaced with the vector median. This process also introduces some distortion to the image.

The MVMF has a two-staged algorithm to solve the shortcoming of the VMF. The first stage requires conducting a local preprocessing test, which involves comparing the computed relative cumulated distances at every window location for all the pixels. This process is to check whether all the pixels in the window are corrupted. If the relative cumulated distances are all equal ($d_1 = d_2 = d_3 = \ldots = d_n$), then the window is increased (from W to W+2 if the maximum window size is not exceeded) and the first step is repeated again. If all the relative cumulated distances are equal it means the pixels are all corrupted. On the other hand, if the relative cumulated distances are different ($d_1 < d_2 < d_3 < d_4 < \ldots d_n$), then the algorithm proceeds to the next step.

The next step compares the relative cumulated distance of the center pixel value with the relative cumulated distance of the maximum value (pixel with the maximum relative cumulated distance), $[D = \|D_n - D_{Center}\|]$. This process is to test whether the center

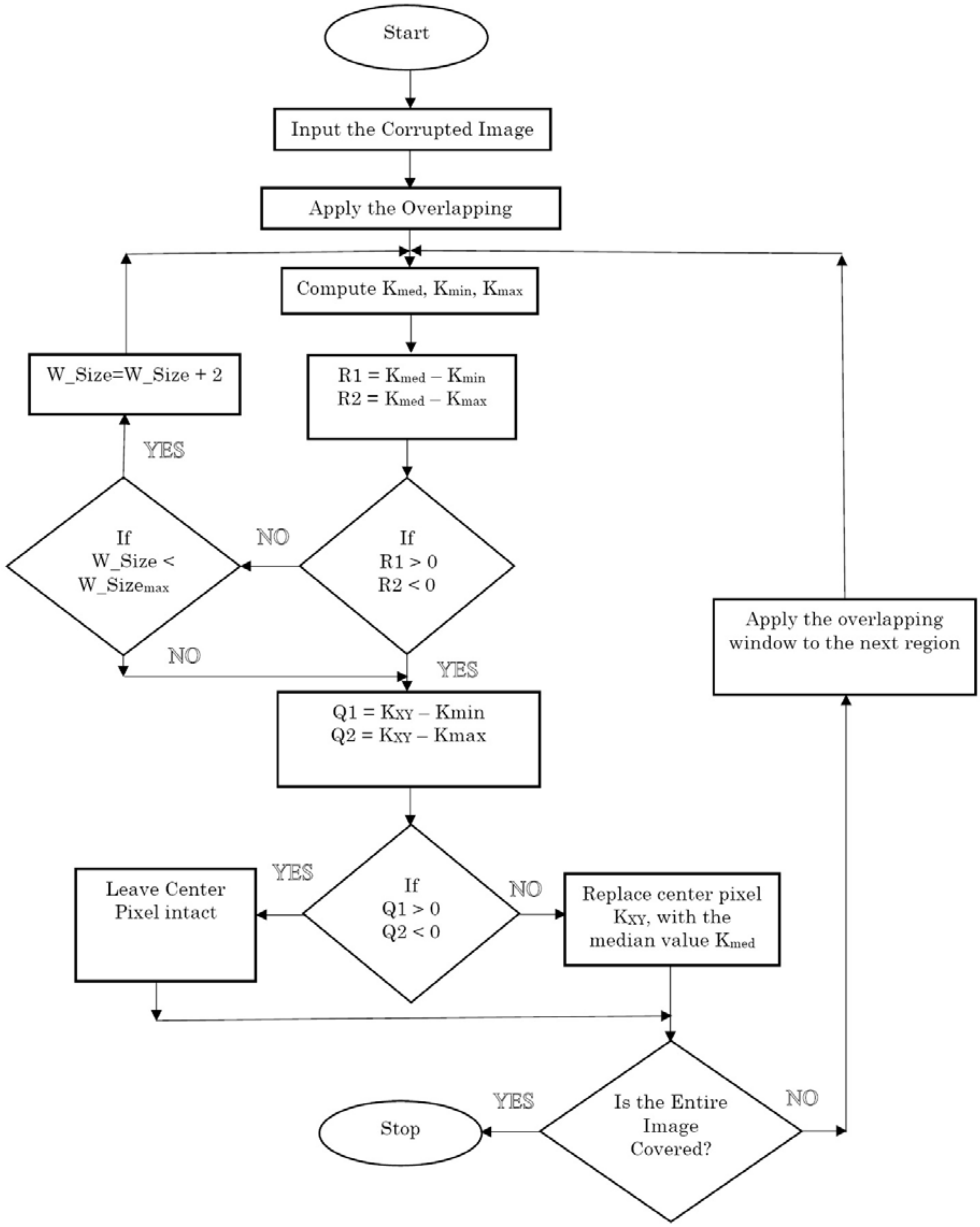

Figure 2. A flowchart of the Adaptive Median Filter

pixel value is corrupted or not. If the relative cumulated distances of both pixels (center pixel and maximum pixel) are equal $[D_n = D_{Center}]$, then the center pixel is considered impulsive and has to be replaced with the vector median; otherwise the center pixel is left untouched. After the process is completed the window is moved to the next location and the same processes are repeated until the window moves through the entire image.

This work, using the MVMF, modifies VMF to achieve a better performance by incorporating a robust noise detection mechanism with a dynamic moving window technique to the VMF. The MVMF approach is to increase the size of the window if the computed Euclidean distance of more than 50% of the pixels in the window is the same. The step of the local preprocessing and the noise filtering is explained in Figure 3. The result of the filtering from this section is fed into phase three. The incorporation of the noise detection and the dynamic window technique is the novelty of this second phase of the filter.

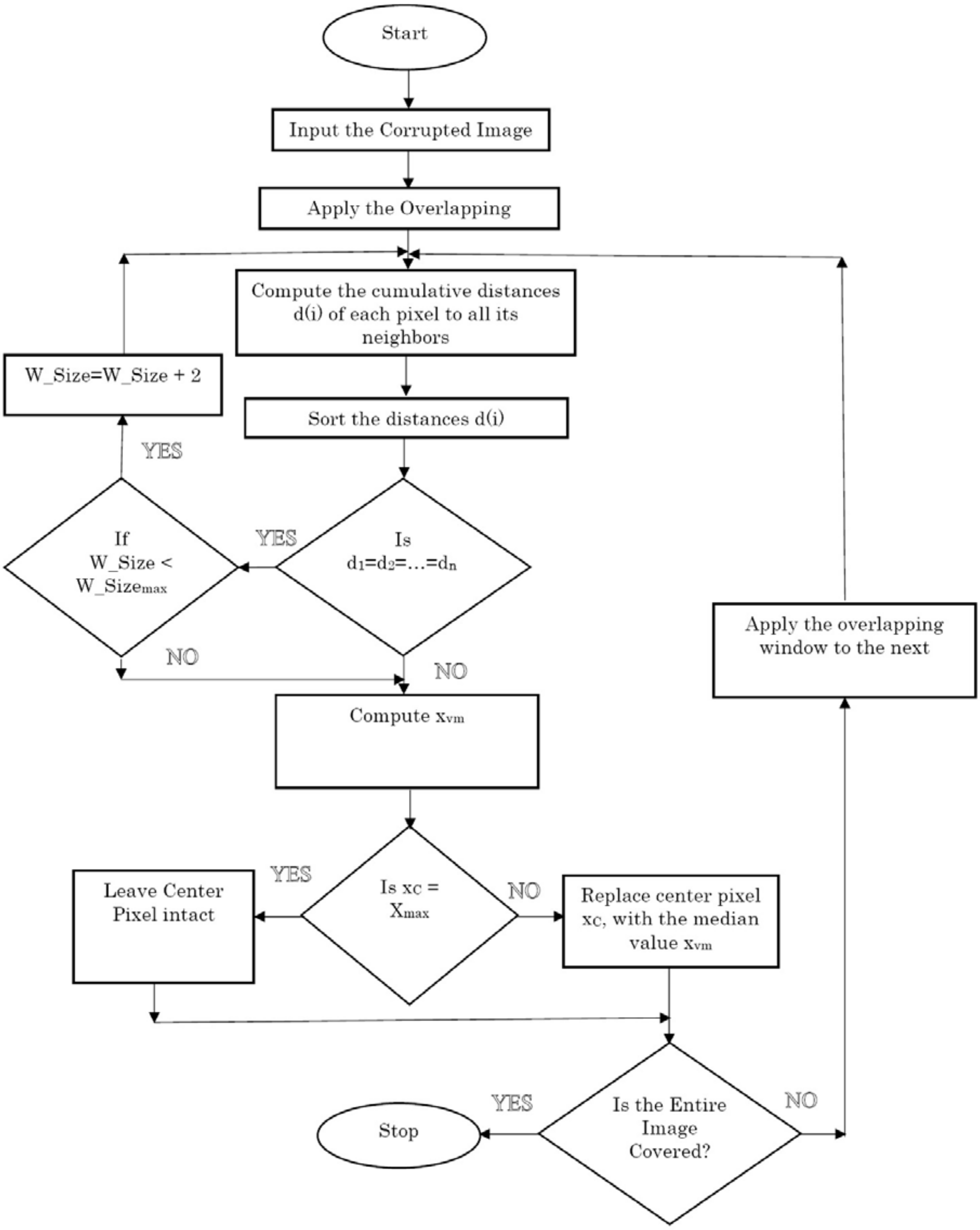

FIGURE 3. A flowchart of the MVMF

Algorithm of the Modified Median Filter

W $\leftarrow$ Window size

$\mathrm{W_{MAX}}$ $\leftarrow$ Maximum window size

D_n $\leftarrow$ Relative cummulative distances associated to a pixel

D_{Center} $\leftarrow$ Relative cummulative distance associated to the center pixel

x_i $\leftarrow$ Pixels in the window

x_j $\leftarrow$ Selected pixel

x_C $\leftarrow$ Center pixel

x_{vm} $\leftarrow$ Vector median pixel

i, j, n $\leftarrow$ Represent the number of the current pixel

1. Let W $=$ 3 be the starting window size.
2. For each pixel in the window compute the distances to all the neighboring pixels using the L2-norm in Equation (2).
   The pixels in the window are x_i, $i = 1, 2, 3, 4, \ldots, N$
$$D = \sum_{i=1}^{N} \|x_j - x_i\|_2 \tag{2}$$
3. Sort the distances computed in descending order. If $d_1 < d_2 < d_3 < d_4 < \ldots d_n$ then select the pixel with the minimum aggregate distance as the median value x_{vm} using Equation (3) and move to step 4.
$$\sum_{i=1}^{N} \|x_{vm} - x_i\| \leq \sum_{j=1}^{N} \|x_i - x_j\| \tag{3}$$
   Else if the all the relative cumulated distances are equal $d_1 = d_2 = d_3 = \ldots = d_n$ then increase the size of the window if $\mathrm{W} = \mathrm{W} + 2 \leq \mathrm{W_{MAX}}$ and move to step 2.
4. Check whether the relative cumulated distances of the center pixel and the maximum value are equal or not. $D = \|D_n - D_{Center}\|$. If they are equal then the center pixel is replaced with the vector median; otherwise the center pixel is left untouched, x_C. And the window moves to the next location and the process continues.

3.3. **Phase three: design of the BMHMF.** The block matching process is the final phase of the BMHMF which is applied to smoothen the image and resolve the color artifacts remaining in the image. The result of the processing in phase two is fed into phase three. The primary task of the block matching technique is to recover the dead or polluted edge pixels as well as recover the corrupted image detail.

The block matching process can detect and fix some undetected distortions in the image. The filtered image is divided into 3–by–3 blocks that are extracted independently. Each 3–by–3 block is matched with its corresponding 3–by–3 block extracted from the noisy image. Three 3–by–3 blocks are extracted from the noisy image. The first one is taken from the exact location as its corresponding block in the filtered image while the second one is taken moving one step away to the left. Then the third one is also taken one step away to the right from the original location. The moving window mechanism is used in obtaining the 3–by–3 blocks in the noisy image. This extraction is done by moving the pivot from pixel to pixel in a stepwise manner. The process is explained below.

1. A moving window is applied in the extraction of a 3–by–3 block patch from the filtered image.
2. Three 3–by–3 blocks are extracted from the noisy image. The first one is taken from the exact location as its corresponding block in the filtered image while the second

one is taken moving one step away to the left. Then the third one is also taken one step away to the right from the original location.

3. The scalar median for each color component is computed for each block. Thus, each block produces three vector components for further preprocessing. After this process, the L2-norm is applied to the nine vector pixels from the 3 extracted blocks of the noisy image. The first three with the minimum aggregate distance are selected for the matching process.
4. The relative cumulated distance between the center pixel and each of the selected pixels is computed. This relative cumulated distance of the center pixel is compared with a threshold. If the distance obtained is greater than the threshold then it is deleted and the pixel with the distance that is less than or equal to the threshold is replaced with the center pixel. Otherwise the center pixel is left untouched.

The idea was adapted from the block matching process of the video processing systems and modified with unique processing steps to recover dead edge pixels as well as restore bright pixels. This method is new and novel since it addresses the problem. Figure 4 gives a clear picture of a detailed framework of the stage in the Block Matching (BM).

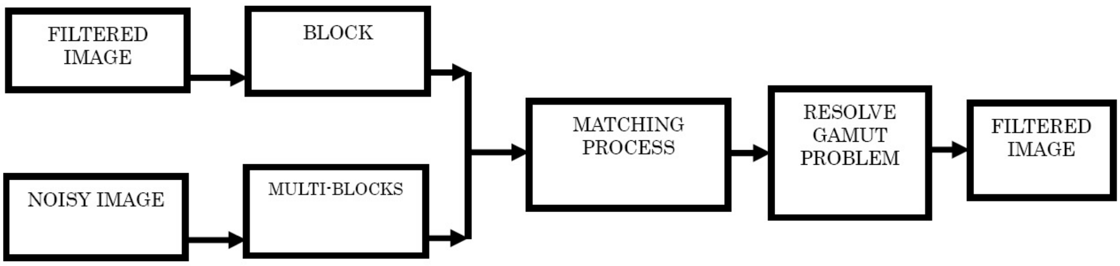

FIGURE 4. Framework of the Block Matching Filtering process

4. **Experimental Results.** In many areas of application such as multimedia, production of motion pictures and printing industries, special emphasis is given to perceptual image quality. However, the perpetual closeness of the filtered image to the original (clean) image is the best measure of the efficiency of a filter. There are two main approaches to evaluating the performance of a filter. They are the subjective analysis shown in Figures 5-7 and the objective analysis shown in Table 2.

4.1. **Subjective analysis.** In Figures 5, 6 and 7 the performance of the designed filter is evaluated using the subjective analysis where the filtered images are compared visually with the original image.

(a) Original Image (b) 10% Noise Corruption (c) Filtered Image

FIGURE 5. Application of the BMHMF on the Lena image corrupted with 10% impulse noise

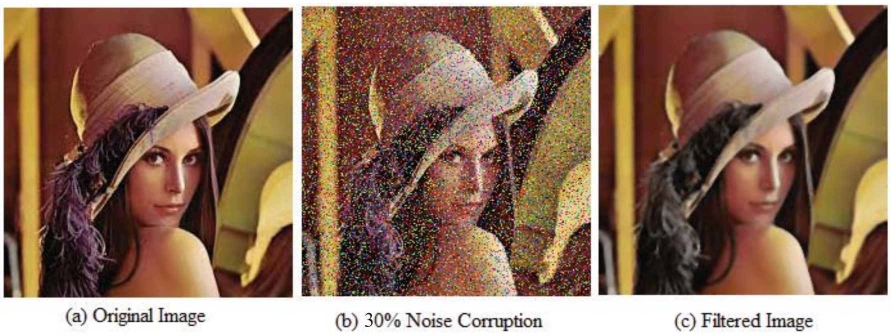

FIGURE 6. Application of the BMHMF on the Lena image corrupted with 30% impulse noise

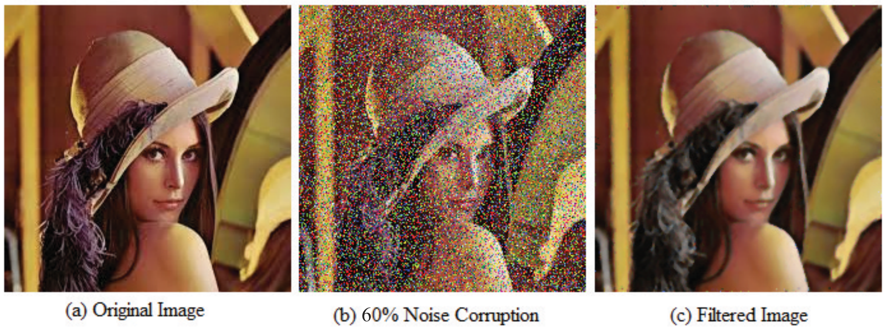

FIGURE 7. Application of the BMHMF on the Lena image corrupted with 60% impulse noise

4.2. **Objective analysis.** A number of quantitative measuring parameters can be employed to evaluate the performance of the various types of filters for restoring damaged signal quality and quantity after filtering out impulse noise (salt and pepper). The Peak Signal-to-Noise Ratio (PSNR) is employed to compare the effectiveness of the proposed BMHM filters [3,4,14,21]. The PSNR is the ratio between the extreme likely power of the clean image signal and the power of damaged noisy signal that affects the reliability of its illustration. Cumulative squared error between the noisy image and the filtered image is the MSE. The mathematical formula for the MSE is:

$$MSE = \frac{1}{mn} \sum_{i=0}^{m-1} \sum_{j=0}^{n-1} [I(i,j) - K(i,j)]^2 \tag{4}$$

where, M and N are the total numbers of pixels in the column and row of the image respectively. Also, I denotes the noisy image and K represents the filtered image. The MSE of zero means an ideal or perfect accuracy. The MSE is an estimator that evaluates the variation between the original image and the filtered image. The smaller the MSE, the better the filter performance in the noise suppression process. Whilst on the other hand the bigger the PSNR, the better the filter performance.

$$PSNR = 10 * \log\left(\frac{255^2}{MSE}\right) \tag{5}$$

The PSNRs for Lena corrupted images were computed after applying various filters shown in Table 2. The image used for this simulation is a benchmark image in the image industry. The simulation was to aid comparison between the proposed filter and the

TABLE 1. Filters taken for comparison with the proposed Block Matching Hybrid Median Filter

S/No.	Acronyms	Filter
1	SMF	Standard Median Filter
2	AMF	Adaptive Median Filter
3	PSMF	Progressive Switching Median Filter
4	DBA	Decision Based Algorithm
5	MDBA	Modified Decision Based Algorithm
6	MDBUTMF	Modified Decision Based Unsymmetric Trimmed Median Filter

TABLE 2. Graphical representation of the PSNR of the filters on the Lena image

Noise (%)	SMF (dB)	AMF (dB)	PSMF (dB)	DBA (dB)	MDBA (dB)	MDBUTMF (dB)	BMHMF (dB)
10	**26.34**	28.43	30.22	36.4	36.94	**37.91**	**38.96**
20	**25.66**	27.4	28.39	32.9	32.69	**34.78**	**35.65**
30	**21.86**	26.11	25.52	30.15	30.42	**32.29**	**32.61**
40	**18.21**	24.4	22.49	28.49	28.49	**30.32**	**31.02**
50	**15.04**	23.36	19.13	26.41	26.52	**28.18**	**29.11**
60	**11.08**	20.6	12.1	24.83	24.41	**26.43**	**27.86**
70	**9.93**	15.25	9.84	22.64	22.47	**24.3**	**25.34**
80	**8.68**	10.31	8.02	20.32	20.44	**21.7**	**23.06**
90	**6.65**	7.93	6.57	17.14	17.56	**18.4**	**21.11**

various state-of-the-art filters mentioned in Table 1. For the outcome of the BMHMF, Figures 5, 6 and 7 present the graphical representation of the results.

4.3. **Analysis of results.** The BMHMF has shown the outcome of the filtering in the subjective analysis, its effectiveness in detecting distortions in the individual RGB color components and its efficiency in correcting distortions. The undistorted correlation of the RGB vector components in the color image are not tampered with. The efficiency of these filters in identifying the distortion in the RGB components is derived from the outcome of the simulations performed on the Lena. From a visual perspective, the results from the subjective analysis show that a greater percentage of the impulse noise induction in the image is detected and filtered. Also, bright and edge pixels are detected and untouched. This effect is evident when the filtered image is compared to the noisy image and the original image.

The objective evaluation is a quantitative analysis of the results obtained. The peak signal-to-noise ratio is employed to calculate the quantitative results of the original image recovered. PSNR of some state-of-the-art filtering methods are compared to the PSNR of the BMHMF. The results of the objective evaluation (Table 2) demonstrate the effectiveness of the BMHMF vis-à-vis SMF, AMF, PSMF, DBA, MDBA, and MDBUTMF. For example, the BMHMF that was applied to the Lena color image corrupted with 10% impulse noise resulted in a filtered image with a PSNR 38.96. And, when SMF was applied to the same corrupted image, the SMF performed poorly with 26.34 PSNR. However, applying the same procedure, the MDBUTMF produced the best result among the reference filters with a PSNR of 37.91. For sequent impulse noise corruption [20%-80%], the BMHMF outperforms the best state-of-the-art filters mentioned with relative high PSNRs. At 90% impulse noise corruption the BMHMF still performs relatively better

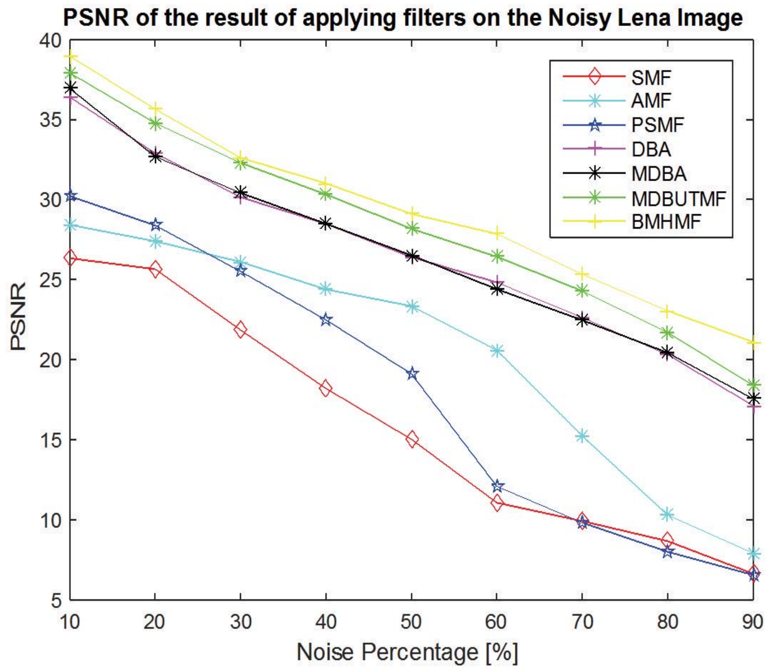

FIGURE 8. Graphical representation of the PSNR of the filters on the Lena image

with PSNR of 21.11 as compared to the best PSNR which lies at 18.33 (MDBUTMF) and 17.56 (MDBA). Figure 8 shows a graphical representation of the behaviors of the filters when applied to the Lena image with different levels of noise corruption [10%-90%].

5. **Conclusions.** This study shows that the Block Matching Hybrid Median Filtering (BMHMF) successfully modifies and combines the operation of three different techniques to achieve an improved hybrid vector filter. This filtering technique performs well from the objective analysis carried out using the peak signal-to-noise ratio as a measure. The filter exhibits an excellent performance balance between details preservation and impulsive noise attenuation in an effective manner. The simulation results show that the filter outperforms the well-known filtering schemes in impulse noise reduction. The BMHMF performs very well when the noise in the image is slightly high [70%-90%]. The filter also demonstrates a strong edge preservation structure shown in the subjective analysis.

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