



## A SURVEY OF IMAGE DENOISING FILTERS BASED ON BOUNDARY DISCRIMINATION NOISE DETECTION

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### ABSTRACT

Image denoising is an essential and complex activity that should be carried out before any other image processing because it checks for errors within the image(s) and rectifies them. There are ways to remove noise, the switching scheme is an outstanding method when equated to others, it initially segregates the noisy pixels and then filters them. Boundary Discriminative Noise Detection (BDND) is a type of algorithm that uses the switching method and is good for impulse noise detection, many works have been presented using several enhancements to detect noise from images using BDND. In this paper, we present a detailed outline of impulse noise and noise removal techniques by looking at over a decade of research conducted to establish a fundamental understanding of the Boundary discriminative noise detector algorithm used in image denoising. We analyzed 19 relevant papers through Google Scholar, focusing on three aspects: the methods for detecting noisy pixels, the type(s) of noise, and the major challenges. We found that many of the image denoising methods still use BDND and at least one algorithm is developed yearly except for 2017 to 2021, indicating the algorithm is significant in the field of image denoising. Furthermore, we wrap up the survey by highlighting some research challenges and offering a list of key recommendations to spur further research in this area.

**General Terms:** Algorithms, Filter, Noise removal.

**Keywords:** BDND, Image Noise, Switching Filter.

### INTRODUCTION

Noise in images can be associated to various sources like variation in detector sensitivity, environmental variation, and transmission. Noise at any level is always undesirable, hence denoising has to be employed before the image could be used for further analysis. One of such techniques for image denoising is the switching technique where noisy pixels are detected in advance then filtered. Boundary Discrimination Noise Detection (BDND) Algorithm is one of the methods that use the switching technique, where every pixel belonging to an image is subjected to a process of detection. A kernel of  $21 \times 21$  dimension is centered on the target pixel, the pixel intensity values will be grouped into three clusters (the upper, middle, and the lower cluster) and the binary decision map is formed using "0s" to denote the locations of non-noisy, and "1s" denoting the noisy pixels. As a result, two essential boundaries are formed. If the pixel in question falls within the middle cluster, it will be considered uncorrupted, given that its intensity value is neither relatively low nor relatively high, else, the pixel may be corrupted by impulse noise. The accuracy of clustering

results ultimately depends on how accurate the identified boundaries are (Pei-Eng Ng & Kai-Kuang Ma, 2006).

The contribution of this paper is to provide a clear outlook of recent advances of BDND algorithm so as to enhance the understanding of researchers on the basis of image denoising algorithm using BDND.

The rest of this paper is structured as follows: first, an explanation of the impulse noise models is given; then a description of the two steps of original BDND; additionally an outline of the works related to BDND are presented.

### Study selection procedure of the articles

Figure 1 shows the search protocol, specifically planned to ensure that a thorough analysis is carried out. The primary search returns 46,600 publications using Google Scholar, reduced to 708 articles based on the title check, reduced to 19 articles, after the abstract check and relationship to image denoising. The 19 selected articles were used based on the full substance of the papers.

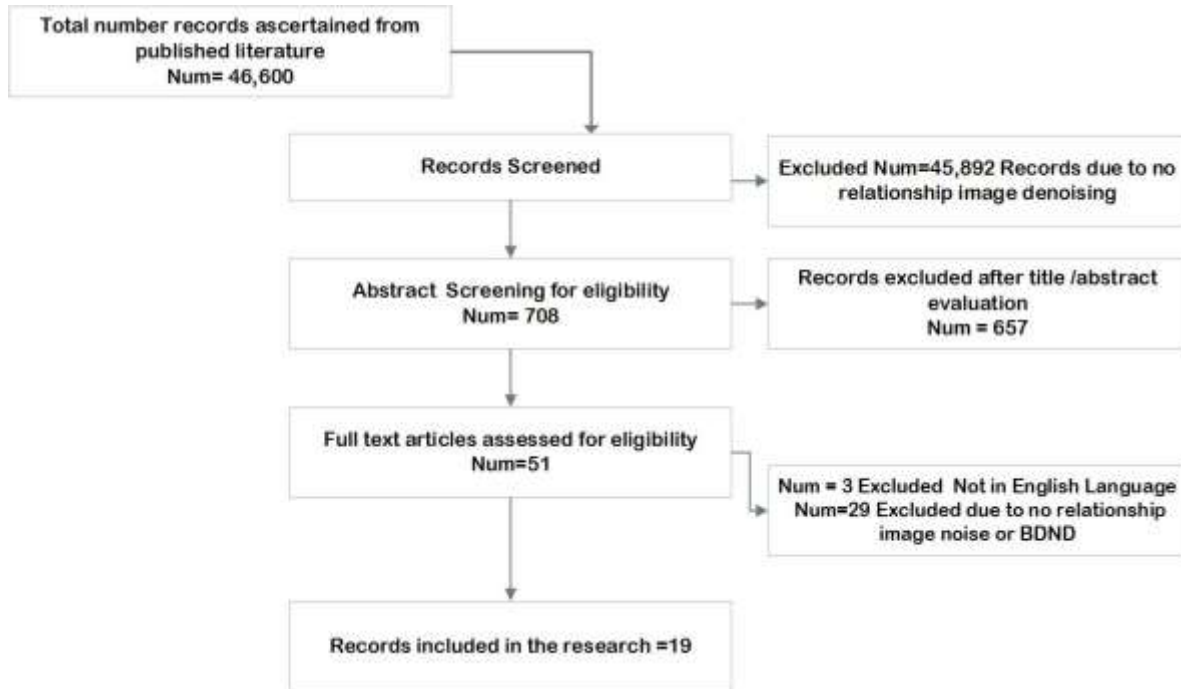


Figure 1 Study Selection process

**Contributions:**

1. We present an updated descriptive literature review on BDND techniques used in image denoising.
2. We provide open research problem and opportunities for future research
3. We also reviewed the evaluation parameters by the research papers in the area of Image processing using BDND.

**Impulse Noise Model**

**Fixed valued impulse noise or Salt-and-pepper noise:** - the corrupted pixels takes either of the two extreme values (i.e. 0 and 255) leading to white and black spots in the image. For this noise model the distribution  $p$  of noise  $N$  is defined as in (Pei-Eng Ng & Kai-Kuang Ma, 2006):

$$p(N) = \begin{cases} 0.5 & \text{pepper ; } N = 0 \\ 1 - p & \text{noise free pixels; } 0 \leq N \leq L - 1 \\ 0.5 & \text{Salt; } N = L - 1 \end{cases} \quad (1.1)$$

**Random Valued Impulse Noise/ Uniform Impulse Noise:** The noisy pixels are corrupted with values within range of [0, 255] for gray-scale images. “Removal of Random valued impulse noise is more complicated due to the random distribution of the noise pixels (Nadeem et al., 2020a). The distribution of the impulse noise is equally distributed. This is also presented in (Nadeem et al., 2020b).

$$W(x, y) = \begin{cases} 0 \text{ to } 255 & \text{corrupted pixel} \\ f(x, y) & \text{non - corrupted pixel} \end{cases} \quad (1.2)$$

**Mixed Impulse Noise or Universal impulse noise:** - The contamination is equivalently influenced by the two most prevalent impulse noise models, which are the Random Valued Impulse Noise (RVIN) and Salt and pepper Impulse Noise (SPIN). The Universal impulse noise model is more realistic. This noise can be described by the following equation from (Pei-Eng Ng & Kai-Kuang Ma, 2006).

$$W(x, y) = \begin{cases} \eta_1(x, y) & \text{with probability } \frac{p}{2} \\ \eta_2(x, y) & \text{with probability } \frac{p}{2} \\ f(x, y) & \text{with probability } (1 - p) \end{cases} \quad (1.3)$$

**Impulse Burst /popcorn/Random Telegraph:** It occurs due to the interaction of frequency modulated signal with other signals from other data sources during a transmission of a single image and corrupt several image pixels in one or more neighboring rows.

### Boundary Discrimination Noise Detection Algorithm

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#### Algorithm 1: Boundary Discriminative Noise Detection

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1. Input: image, image_width, image_height
2. w = image_width
3. h = image_height
4. binmap  [] =  $\Phi$ 
5. window = 3x3
6. Output: Binary Map
7. for i in w
8.     for j in h
9.         apply window centered on the xij
10.        neigpixel [] = [Xi-1,j-1, Xi-1,j, Xi,j-1, Xi,j, Xi,j+1, Xi-1,j+1, Xi+1,j, Xi+1,j+1]
11.        v0 = sort (neigpixel)
12.        vD = intensitydifference (v0)
13.        set_sbnpath = v0
14.        maxpixel1 = max (vD_0, vdmed)
15.        b1 = indexof (maxpixel1, v0) - 1
16.        maxpixel2 = max ( vDmed, vd_n)
17.        b2 = indexof (maxpixel2, v0) - 1
18.        if b1 < xij < b2 then
19.            xij is noise-free
20.            binmap[i][j] = 0
21.        else
22.            if window == 3x3
23.                binmap[i][j] = 1
24.            else
25.                window = 3x3
26.                apply window centered on the pixel
27.                repeat 8-13
28.            endif
29.        endif
30.    endfor
31. endfor

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### The Filtration Stage

In the filtration stage, the Noise Adaptive Switching Median (NASM) (Eng & Ma, 2001) was exploited to replace only the noisy pixels identified by the BDND. It was developed to solve the problem of replacing the identified noisy pixel with a wrong pixel value, which could occur when using a smaller window size due to increase in the number of corrupted pixels in the window. Therefore, the window is enlarged in four directions until the total of uncorrupted pixels in the window is more than half the pixels or reaches the final size of the window.

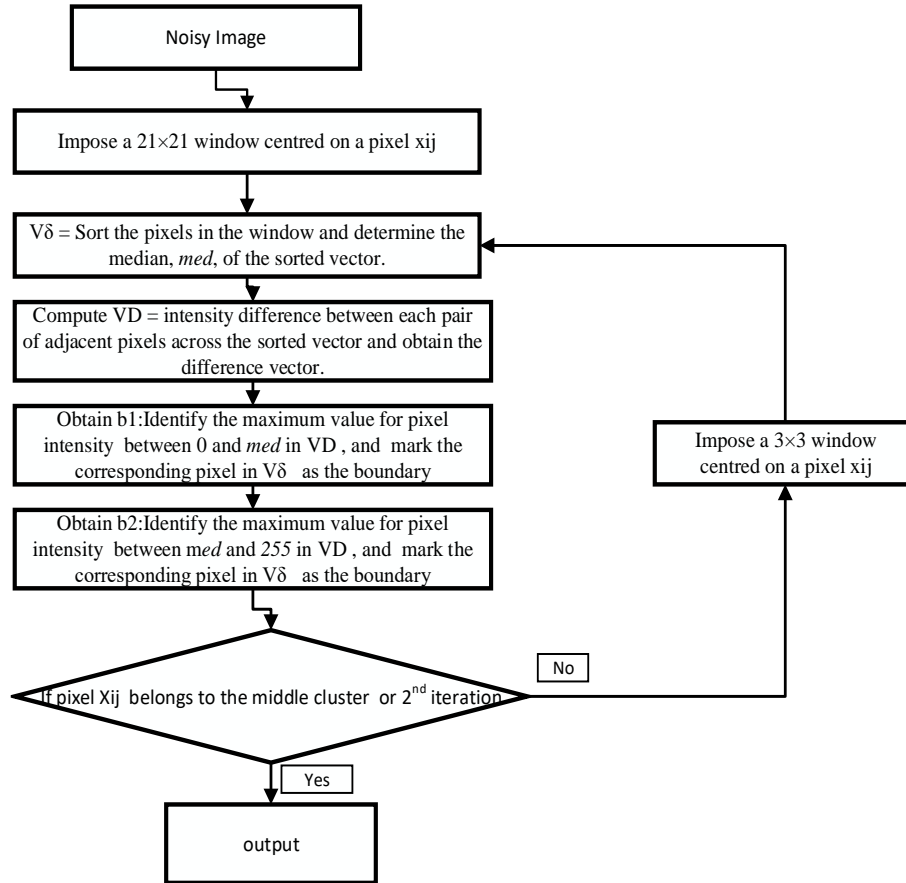


Figure 2 Boundary Discrimination Noise Detection Flow Diagram

### LITERATURE SURVEY

Review of previous studies revealed that, no systematic survey was carried out, regarding the use of the BDND algorithm for image denoising. Table 1 summarizes the prominent works carried out on this area of image denoise using BDND and emphasizes their focus and weaknesses.

The work of (Ng & Ma, 2006) developed switching median filter using BDND algorithm, the detection starts with BDND using a  $21 \times 21$  window, centering on the target pixel and classifying the pixels as low-intensity impulse noise (lower cluster), uncorrupted (medium cluster), and high-intensity impulse noise (higher cluster). If the target pixel falls in the lower or higher cluster, it is presumed to be noisy or corrupt, and then the procedure is repeated using a  $3 \times 3$  window and in the filtration Modified Noise Adaptive Switching Median (NASM) filter. Simulation results show that the filter consistently outperforms the NASM filter by achieving a much higher output. It was able to boost noisy pixel detection, especially for salt and pepper noise. Though, the overall time consumption, false alarm, and missed detection increased at a high noise level (Chen, Hung, & Zou1, 2017) (Sarvesh et al., 2021).

In the work of (Ping et al., 2007) the modified BDND was presented to reduce the computational time of BDND, in the detection stage, the boundaries are determined by calculating the local window histogram where the bin indices are the gray

levels, the first boundary  $b1$  is determined by computing the difference of non-zero adjacent bin indices between min and med, then determining the maximum difference and mark the corresponding index, same is done from med to max for  $b2$ . For filtration, if the number of uncorrupted pixels in the filtering window exceeds 3, the extension ends. Experimentally, the system accomplished better running time and better PSNR value at higher noise density, but BDND was better at denoising at lower density.

The work presented by (Hsieh et al., 2009) proposed a denoising scheme that concentrated on improving both the detection and the filtration stage. In the detection stage, if the maximum value of the absolute intensity values between min to med is 0, then adjust  $b1 = b2$ . On the other hand, when the maximum value of the absolute intensity values between med to last is 0, then reset  $b2 = b1$ . Increase the window to a  $7 \times 7$  dimension and redo the steps then classify, but when there is only a single non-zero value in absolute intensity values then change  $b2 = b1$ . The filtration starts with a  $3 \times 3$  checking for uncorrupted pixels if more than one uncorrupted pixel exists then calculate the median value of all uncorrupted pixels and replace the noisy pixel with the median value, if only a single uncorrupted pixel exist then substitute the noisy pixel by it. Else expand the window and check again. The result of the experiment showed BRBDND/MFSW performed better in terms of visual quality and PSNR. However, there is an increased False alarm for unbalanced salt and pepper

In (Nasimudeen et al., 2012) The algorithm removes all pixel values below the  $b_1$  and above  $b_2$  leaving only the middle cluster intensity values, if what is left does not contain a value, the minimum and maximum values will be set as  $b_1$  and  $b_2$ , otherwise  $b_1$  and  $b_2$  will be the new minimum and maximum values of the reduced list. Only pixels contained in the middle cluster are classified as uncorrupted, this is used to form a binary map. An advanced adaptive switching filter based on the four key directions was developed in the filtration stage, using a  $3 \times 3$  window, and expanding by two pixels outward if the quantity of uncontaminated pixels inside the window is less than half. The system achieved a reduced processing time unfortunately, the relationship between the pixel values is likely lost as the window size increases during filtration.

Another work was presented by (Haidi Ibrahim, 2011) titled modified BDND, it creates two local histograms corresponding to a  $21 \times 21$  and a  $3 \times 3$ , it uses local cumulative density function to calculate the median, then finds the largest bin gap between 0 to med and the corresponding intensity value is  $b_1$ , from med to 255 the corresponding intensity value of the largest bin gap is  $b_2$ . In both the detection and the filtration stages, the global noise density estimation is used to decide the total number of local histograms used. Although it was able to reduce the computation time, it had a similar result as BDND.

Another work also presented a combination of the Local outlier factor, a density-based outlier detection method, and BDND. In the detection stage, the LOF value of each pixel is checked whether it is higher than the first threshold value, if it is higher it is considered as noise, then BDND is invoked to check using a  $21 \times 21$  window if it is still assumed to be the noise it then goes through a validation stage where it is checked against the second threshold value. If it is higher, BDND is invoked using a  $3 \times 3$  window. For the filtration stage, the directional weighted median filter (DWMF) is used. LOFBDND had an enhanced performance in terms of the PSNR and reduced missed detection compared to the contending methods but increased false detection compared to BDND (Wang & Lu, 2011)

ABDND was presented by (Tripathi et al., 2011), the detection starts by calculating the forward difference between two adjacent histogram counts to form a difference array,  $t_1$  is the index corresponding to the negative maximum and  $t_2$  is the max index corresponding to the positive max in the difference array. The difference between the concerned pixel and the minimum intensity value in the window and the difference between the concerned pixel and the maximum intensity value in the window is checked against  $t_1$  and  $t_2$  respectively, If greater than the thresholds, it is assumed to be noise, after this the noise map refinement is invoked where final noise map is determined. Finally, an adaptive switching median filter is used for filtration. ABDND accomplished a good result but has increased false detection at very-low-density noise compared to BDND.

NBLDND was proposed by (Zuviria et al., 2012) to suppress salt and pepper noise at a very high density. It uses the same initial step of BDND in the detection stage, if the pixel is assumed as noisy, the noise density is determined and the detection window based on the noise density is placed around the pixel and the steps of BDND are repeated. In the filtration stage of NBLDND, the algorithm initiates an extra vertical

window size and a horizontal window, these windows are checked until a noise-free pixel is found within the neighborhood to replace the noisy pixel. NBLDND accomplished an improved visual quality and decreased processing time. However, artifacts are introduced in some cases.

In (Jafar et al., 2013) the work improved the accuracy of filtration stage by considering the sum of uncorrupted pixels inside the filtering window. A simple change to the condition was made, only expanding the window when the total number of uncorrupted pixels within the filtering window is zero or less than half the pixels and maximum window size has not been reached and during the calculation of the approximated pixel values, the spatial relationship between the noisy pixel and the uncorrupted pixels in the window and the relationship between the values of the uncorrupted pixels and the central pixel is considered. An enhanced performance was shown on the visual quality of the filtered image.

“Non-local means filter for removal of high-density RVIN and Salt and pepper noise was introduced by (Nasri et al., 2013). For the latter, the original BDND and simple detection were used in the detection stage. In the filtration stage, two different windows are considered the bigger window called the search window and the smaller is known as the patch window, the repaired value of the pixel in concern is gotten as the weighted sum of all non-noisy pixels which are based on a similar patch in the search window. A non-adaptive window was used in the filtration, and this made the method non-responsive to high-density noise.

The method in (Verma & Singh, 2013), was developed with the aid of three membership functions, fuzzification is integrated into BDND noise identification, each rule is given a weight for verifying whether a pixel is distorted by noise or not, therefore forming a binary map. Later, a confirmation is done using a  $5 \times 5$  window. Noisy pixels are then filtered using the median of non-noisy intensity value in the window, based on the requirement that the number of uncorrupted pixels should be greater than or equal to half of the total number of pixels in that particular window the size of the window is raised from  $3 \times 3$  to  $7 \times 7$ . Showed a significant improvement but blurs the image at above 50% noise density.

The paper by (Huang et al., 2013) MABDND is an improved ABDND that aims to eliminate random-value noise of high density. There are two components for the detection stage, noise detection and non-noise detection. For noise detection, it utilizes the same process as ABDND. The non-noise detection step is a verification component using histogram statistics from the first stage to classify pixels of false detection as corrupted or uncorrupted pixels. MABDND results show a decreased false detection and low MD when compared to ABDND.

The work of (Shalimettilsha & Kumar, 2014) In this work, the estimated noise density, total number of pixels in the filtering window are calculated, if the total sum of uncorrupted intensity value is below half of the percentage of noisy pixels in the filtering window is expanded outward by one pixel in all directions. The median of the uncorrupted pixels in the window is calculated and adjusted according to the spatial value using the Cubic interpolation.

“Modified Boundary Discriminative Noise Detection” (MBDND) was presented by (Thanakumar et al., 2014)) was proposed to decrease the expansion of window size and spatial relationship should be used in the pixel replacement during filtering, to do these the window is expanded only when any of the two windows are violated (i) if number of uncorrupted pixels is  $\geq$  half of the number of pixels in the window. (ii) number of the uncorrupted pixel is not equal to zero and finally for the estimation of pixel. However, under high noise densities, the first condition demanding the number of uncorrupted pixels to be more than half of the number of pixels in the window is easily violated. Thus, with high noise densities, the filtering window is expected to be expanded and most likely it will reach the maximum size. However, such a requirement is hard to satisfy under high noise densities.

The work of (Sharma & Pateriya, 2015) improved BDND in the detection stage by modifying the second iteration using a  $3 \times 3$  window, if the target pixel isn't an extreme value, then the pixel is uncorrupted, but if the center pixel is 0 and window contains intensity value order than the two extreme values then calculate weighted median intensity values and finally, if window contains only the two extreme values, the number of zeros and 255 will compared then the noisy pixel is replaced with the highest number i.e. (0 or 255).

Regression Based Color Noise Estimation and Removal with Improved BDND Algorithm by (Sendhilkumar & Pandurangan, 2017) was proposed to refine Modified Boundary Discriminative Noise Detection (MBDND) by (Thanakumar et al., 2014) by relaxing the condition a bit and taking into consideration the estimated noise density which is determined from the detection step of the algorithm and the total number of pixels in the filtering window by using linear regression. The authors reported the algorithm tolerates up to 90% of the noise and high PSNR obtained of up to 30db.

Another work proposed a modified BDND algorithm to improve detection at higher impulse noise density. In the filtering stage the sum of uncontaminated pixels within a window is determined, if the sum of uncontaminated pixel is above zero, then, the Euclidean distance between the centered pixels and the uncorrupted pixels is calculated and converted to distance weight. The noisy pixel is substituted by the sum of the product of distance weight and all the uncorrupted pixels (Sangave & Jain, 2017).

In (Rani & Satyanarayana, 2017)“This Boundary Discrimination Noise Detection with switching bilateral filter (BDNDSBF) was developed to be able to filter mixed noise (a combination of Gaussian and impulse noise). It is a two stage method, the detection and the filtering stage. In the detection stage BDND is used to segregate the noisy from the non-noisy pixels then generate a two-dimensional binary decision map. The image and the output of BDND is passed to Switching Bilateral Filter is employed to detect the edges, edge information and classify noisy pixels as either impulse or gaussian. The filtration is similar to SBF (Chih-Hsing Lin et al., 2010).

In the work of (Sarvesh et al., 2021) every iteration considers a local window ( $3 \times 3$ ) to establish  $b_1$  and  $b_2$  boundaries by determining the window's contrast value.  $Contrast/2$  describes  $b_1$ , and  $median + contrast/2$  describes  $b_2$ . If a pixel value is outside the range of  $b_1$  and  $b_2$ , it is referred to as corrupted, whereas pixels that are within the bounds are referred to as uncorrupted. The binary matrix is created by assigning 1 to corrupted pixels and 0 to uncorrupted pixels. The noisy pixel's value is replaced with the window's median value in the related image, while uncorrupted pixel values remain intact.

The summary of these finding are presented in Table 1, it tabulates the author of each denoising method, name of method if available or name of paper, reason for modification, filtration method, algorithms used for comparison and finally the limitation of the method.

**Table 1: Summary of the Literature, Noise type, Filtration, limitations**

S N	Reference	Name of Method	Purpose/ reason	Noise type	Filtration	Algorithm m compared	limitation
1.	(Sarvesh et al., 2021)	Removal of Noise in an Image using Boundary Detection Technique	Noise removal and edge preservation	Salt and Pepper	Median	WMF, AMF, BDND	Increased MSE values in some images
2.	(Rani & Satyanarayana, 2017)	A New Proposed Modification on the BDND Filtering Algorithm for the Removal of High Density Impulse Noise	better accuracy in noise detection	Mixed Noise	SBF	SBF, BDSBF	-Same as BDND -large black spots on the filtered image
3.	(Sangave & Jain, 2017)	Impulse Noise Detection and Removal by Modified Boundary Discriminative Noise Detection Technique	Improve accuracy in noise detection	Impulse Noise	Euclidean distance algorithm	WMF, AMF, DBA, IDBA PA	Increased execution time
4.	(Sendhilkumar & Pandurangan, 2017)	Regression Based Color Noise Estimation and Removal with Improved BDND Algorithm	Improve filtration of the noisy pixels	Salt and pepper noise	Noise Adaptive Switching Median with window expansion	-	-Increased execution time

5.	(Sharma & Pateriya, 2015)	Removing Salt and Pepper Noise using Modified Decision- Based Approach with Boundary Discrimination	Enhance detection and filtration of the noisy pixel.	Salt and pepper noise	weighted median	-	-Increased blurring
6.	(Thanakumar et al., 2014)	High Density Impulse Noise Removal Using BDND Filtering Algorithm	Improve performance of the process	Salt and pepper noise	Modified Noise Adaptive soft Switching Median (MNASM)	MBDND, PSMF, BDND,C WMF, ATMF	-blurring in the filtration stage for high density noise
7.	(Shalimettilsha & Kumar, 2014)	A New Proposed Modification on the BDND Filtering Algorithm for the Removal of High Density Impulse Noise	advance image quality and increase the performance of the BDND algorithm		Filtration using spatial and intensity information.	-	
8.	(Huang et al., 2013)	Modification Of Advanced Boundary Discriminative Noise Detection (MABDND)	Reduce miss detection and false detection in ABDND	Salt and pepper	Adaptive Switching Median Filter (ASMF)	ASMF, BDND,AB DND, DAWSM	-increased running time when compared to BDND
9.	(Verma & Singh, 2013)	A Fuzzy Impulse Noise Filter Based on Boundary Discriminative Noise Detection.	improved performance of BDND	Impulse Noise		ASWM, BDND, SMF, DBAIN	Blur image at noise density above 50%
10	(Nasri et al., 2013)	SNLM: A switching non-local means filter for removal of high density salt and pepper noise	Increase the removal of high-density salt and pepper noise	Salt and pepper	Switching Non-Local Means Filter (SNLMF)	PSMF,GP LRC,DBA MDBUT MF	-Not responsive to high density noise
11	(Jafar et al., 2013)	Improved Boundary Discriminative Noise Detection (IBDND)	Improve the filtration stage	Impulse Noise	-IBDNDF	BDND	
12	(Zuviria et al., 2012)	Neighborhood based layer discriminative noise detection (NBLDND)	Improve noise detection in extreme noise cases	Salt and pepper		BDND	artifacts are introduced in some cases of high noise density
13	(Tripathi et al., 2011)	Advanced Boundary Discriminative Noise Detection	Improve detection at high noise density			MRD,Min -Max ,fuzzy, IASMF, MASMF, PSMF, BDND,lap lacian	-high rate in false detection -Low quality restoration image.
14	(Wang & Lu, 2011)	Local Outlier Factor Boundary Discriminative Noise Detection(LOFBDND)	Lower miss detection rate and false detection rate	Salt and pepper	Directional Weighted Median filter	ISM,DWM, ASWM, BDND	
15	(Ibrahim et al., 2011)	Boundary discriminative noise detection(Histogram)	Reduce processing time	Salt and pepper	-	SM, BDND	high rate in false detection
16	(Nasimudeen, et.al, 2010)	Boundary discriminative noise detection by elimination (BDNDE)	Reduce high misdetection, false alarm rate and time complexity	Impulse Noise	Advanced Adaptive switching filter based on the four key directions	BDND	-blurring due to filtering window expansion

17	(Hsieh et al., 2009)	Boundary Resetting BDND and Median Filtering with Smallest Window(BRBDND/MFSW)		Balance d SPN, Unbalanced SPN	Median Filtering With Smallest Window (MFSW)	BDND	Increased False alarm for unbalanced SPN
18	(Ping, et.al, 2007)	Modified Boundary discriminative noise detection	Reduce the time execution time	Impulse noise	Improved Noise Adaptive soft Switching Median (NASM)	7x7 standard median filter, BDND	
19	(Ng & Ma, 2006)	A Switching Median Filter With Boundary Discriminative Noise Detection for Extremely Corrupted Images	Develop a New impulse noise detector	Impulse noise	Noise Adaptive soft Switching Median (NASM)	NASM	-Execution Time is high -High false alarm and missed detection at high noise density.

**Metrics of image denoising Method**

- i. Peak signal-to-noise ratio (PSNR) : The higher PSNR value the better quality of the image
- ii. Mean Squared Error (MSE): The smaller the value the better.
- iii. Mean Absolute Error (MAE): The value ranges from 0 to infinity. The Smaller the value the better.
- iv. Root Mean Square Error (RSME): Ranges from 0 to infinity. The Smaller the value the better.
- v. Structural Similarity Index (SSIM): The larger the SSIM value the better.
- vi. Figure of Merit (FOM): The higher the value of FOM the better.
- vii. Image Enhancement Factor (IEF): The higher value of IEF the better.

Table 2 shows the metric(s) used by each work to indicate its performance. Approximately, more than three-quarter (3/4) of the studies were measured using peak signal-to-noise ratio, two used the MSE, another two used the MAE, one used SSIM, two used the FOM while only one used the IEF, indicating that the PNSR is the most used metrics used at the time of this literature review, probably it is because it is one of the common and easiest error metrics. The parameters such as the SSIM, IQI, and FOM are used for measuring overall image quality, structure, and edge preservation, but they receive less attention.

**Table 2: Summary of the Metric used for each article**

SN	References	PNSR	MSE	MAE	SSIM	FOM	IE F
1.	(Sarvesh et al., 2021)	✓					
2.	(Rani & Satyanarayana, 2017)	✓			✓		
3.	(Sangave & Jain, 2017)	✓	✓				
4.	(Sendhilkumar & Pandurangan, 2017)	✓					
5.	(Sharma & Pateriya, 2015)						
6.	(Thanakumar et al., 2014)	✓	✓			✓	✓
7.	(Huang et al., 2013)						
8.	(Verma & Singh, 2013)	✓					
9.	(Zuviria et al., 2012)	✓					
10.	(Nasri , et.al. 2012)	✓		✓			
11.	(Jafar & Na'mneh, 20127)	✓				✓	
12.	(Tripathi et al., 2011)	✓					
13.	(Wang & Lu, 2011)	✓		✓			
14.	(Haidi Ibrahim et al., 2011)						
15.	(Nasimudeen, et.al, 2010)	✓					
16.	(Hsieh et al., 2009)	✓					
17.	(Ping, et.al, 2007)						
18.	(Ng & Ma, 2006)						



## OPEN CHALLENGES

Based the survey some open challenges where identified and listed below:

1. Determination process of the two boundaries is too rigid: there is no flexibility in defining the two boundaries  $b_1$  and  $b_2$  in the BDND algorithms
2. The large window size in the detection stage which increases the processing time: The  $21 \times 21$  window size which is initially in classifying a pixel is large, therefore increasing the time during processing because of the sorting.
3. Misclassification of pixels (noisy or not noise): classifying noisy pixels as non-noisy pixels or vice-versa.

## RECOMMENDATION

Based on the open challenges presented, some recommendation to address the challenges are itemized below:

1. To solve problems of determining the two boundaries fuzzy method and metaheuristic algorithms could be exploited.
2. In the case of misclassification machine learning algorithms could also serve as a profound solution.
3. Edge detection could be used to reduce the probability of seeing an edge pixel as a noisy pixel
4. In the future, non-linear filtering techniques based on mathematical morphology may be considered to improve the noise detection scheme's performance.

## CONCLUSION

In this survey, impulse noise models were discussed, denoising filters based on BDND were presented, and the metric used in measuring the performance these techniques were also presented. Furthermore, open challenges and recommendations are given. With this survey, pioneer researchers in image processing can be able to ascertain which of the denoising methods presented in this survey will be the best based on robustness of the technique and noise type, and determine which model and denoising method they could use or improve.

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