DSP Filters and Quality Metrics for Image De-noising

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***Abstract*— Digital image processing (DIP) has a much broader scope of tools, techniques and algorithms than the corresponding analog image processing. This valuable advantage can be invested in processing and restoring informative image out of distorted one, for instance noisy image. The main objective of this paper is to insure accurate quality metrics to measure spatial filtering techniques in estimating an actual image out of noisy data. The image is distorted with Salt & Pepper noise. The proposed restoration techniques include Mean filter, Median filter, Max filter, Min filter and Wiener filter. The filters are investigated versus the grayscale image. Different quality metrics are employed, including, Mean Square Error (MSE), Performance Index (PI), Peak Signal-to-Noise Ratio (PSNR), and Image Enhancement Factor (IEF). Moreover, blind metrics that include BRISQUE and NIQE are studied and their accuracies get assessed. Constantly, the investigated quality metrics show that Median filter demonstrates a greater outcome than all of its counterparts. Study shows also that the accuracies of quality measures are in agreement with each other as well as with the subjective assessment of the restored images**.

Keywords: estimation techniques, quality metrics, and Salt & Pepper noise

INTRODUCTION

An image can be considered as a function f(x, y); its value (intensity) at any point is called the image gray level. While the values of x, y and f are finite and discrete, the image is called digital image. Digital computer is used to process digital image, therefore, the whole course is called Digital Image Processing (DIP). DIP includes the main following steps, which are to acquire the image by digital camera, analyze and manipulate the image, as well as conduct image enhancement and restoration [3]. Restoring an image is the final output after all of the related processes of altering image or obtaining a correlated report that is based on an image analysis, understanding and recognition.

Image de-noising (noise removal) is an essential processing role. It is a process by itself and a part in other processes. Numerous tools and techniques are available to recover an image out of noisy data. In fact, this approach can be applicable on any other set of noisy data. Noise removal should be optimum and restored image be intelligent by maintaining its edges for informative details. This can be established by a successful de-noising model of high characteristics quality.

Usually, there are two forms of models, specifically linear and non-linear models, where linear models are most used. The major advantage of linear de-noising models is the efficiency. On the other side, their drawback is the decrease of effectiveness, meaning they are unable to preserve edges successfully. This leads to type of image blurring, where informative details are wiped out. However, non-linear models can manage edges much more effectively than linear models. For example, a well known model for nonlinear image noise-removing is the Total Variation filter (TVF) [1] [2]. The other aspect of restoring an intelligent image is the measurement criteria (quality metrics) that qualify the filtering techniques. Four objective quality metrics are introduced in this study to evaluate the performance of the proposed filters. These will be well compared and tested against each other and additionally versus the subjective evaluation of the images. Further explanation will be presented on the measurement criteria in the following section.

Last but not least the noise, noise in images may have different types, causes and resources. It can be produced by the sensors and/or the image processes. It is the arbitrary change of intensity (brightness) or color information in images created by the sensor. Image noise can also originate in film grain and in the unavoidable shot noise of an ideal photon detector [4]. Image noise can be considered as an unwanted by-product during image acquisition. The most common types of noise may include Salt-and-pepper noise, Gaussian noise, Uniform noise, Speckle noise, etc.

Salt & Pepper noise characteristic is having dark pixels in bright areas and bright pixels in dark areas within an image [4]. This type of noise is caused by dead pixels, A/D converter errors, transmission bit errors, etc. This can be removed by using dark frame subtraction and by interpolating around dark/bright pixels [10] [14], as well as through other spatial filtering techniques that will be discussed in detail by this study. Salt-and-pepper noise is employed here for corrupting an image so that the proposed filters will be employed to

remove the noise. In turn, the quality measures will be assessed on how qualified they are to validate the performance of the filtering techniques.

The remainder of the paper is structured as follows. Spatial filters are introduced in Section II. Section III describes the quality metrics. Results and discussions are presented in Section IV. This section will display how effective the candidate filters in removing noise. The quality measures will be investigated for their reliability of evaluating the de-noising (restoration) techniques performance. Finally, conclusions are extracted in Section V.

SPATIAL FILTERS

A. Mean Filter (MF)

MF is a linear filter, intuitive and easy to execute. MF is the method of computing the average image pixels within the corresponding nearby image pixels . It is to diminish the intensity difference between neighboring pixels. The concept of mean filtering is simply to substitute each pixel value in an image with the mean of its neighboring pixels, including itself. This algorithm will eliminate the impact of pixel values that are not related to their surroundings. Since the mean filtering is often considered as a convolution filter, therefore, it is positioned around a mask. This mask stands for the shape and size of the pixel neighborhood to be sampled when calculating the mean. MF can be defined as simple as
MF (x1 ... xN) = Σ xi/N, where (x1 ... xN) is the image pixel range.

B. Median Filter (MDF)

The MDF is a nonlinear digital filtering technique, often used to remove noise. Such noise removal is a usual pre-processing move to enhance the results of later processing such as edge detection on an image. The MDF advantage is to maintain fine details while removing noise. Therefore, it is often used in digital image filtering applications.

One of MDF characteristics is to work on an image pixel by pixel, substituting each pixel with the median of neighboring pixels. A main advantage of MDF over linear filters is that MDF filter can remove the impact of noise values with very large magnitudes. On the opposite, linear filters are responsive to the noise so that the restored (output) image may be degraded harshly by even the smallest portion of irregular noise values [6]. The 2-D MDF filter utilized in image processing can be introduced by the following equation:

$$\hat{f}(x,y) = \underset{(s,t)\in S_{xy}}{median}\{g(s,t)\} \tag{1}$$

Where (s, t) ∈ w, w represents a neighboring pixels defined by the window size, centered around the pixel (x, y) in the image.

C. Max Filter (MXF)

MXF picks the magnitude of the restored pixel (output) to be the highest value among the neighboring input pixels of the window. Peeper noise (black pixels in an image) can be removed by this filter, but it is not efficiently working against Salt noise (white pixels in an image).

D. Min Filter (MNF)

MNF picks the magnitude of the restored pixel (output) to be the lowest value among the neighboring input pixels of the window. Salt noise (white pixels in an image) can be removed by this filter, but it is not efficiently working against Pepper noise (black pixels in an image).

E. Wiener filter (WF)

The objective of the WF is to remove noise that has distorted an image. It is built on a statistical approach. Usually filters are intended for a desired frequency response. The WF approaches filtering process from different views. One view is assumed to have knowledge of the spectral properties of the original signal and the noise. The second view seeks the linear time-invariant (LTI) filter whose output would come as close to the original signal as possible [1] [7]. WF can be described by the following:

- Assumption: Signal and additive noise are stationary linear random processes with known spectral characteristics.
- Requirement: The filter must be physically realizable, that is causal. This requirement can be dropped as needed, resulting in a non-causal solution.
- Performance criteria: Minimum mean-square error.

The Wiener filter in the Fourier Domain is:

$$G(u,v) = \frac{H^*(u,v)P_{s(u,v)}}{|H(u,v)|^2 P_s(u,v) + P_{n(u,v)}} \tag{2}$$

Dividing through by $\mathbf{P_s}$ makes its behavior easier to explain:

$$G(u,v) = \frac{H^*(u,v)}{|H(u,v)|^2 + \frac{P_{n(u,v)}}{P_{s(u,v)}}} \tag{3}$$

Where:
H(u, v) = Degradation function
H*(u, v) = complex conjugate of degradation function
$P_n(u, v)$ = power spectral Density of Noise.
$P_s(u, v)$ = power spectral Density of un- degraded image.
The term P_n/P_s can be interpreted as the reciprocal of the signal to- noise ratio.

QUALITY METRICS

Image quality can be degraded mainly because of distortions during image acquisition and processing. Examples of distortion causes include noise, blur, ringing, and compression artifacts. Efforts have been made to design objective measures of testing and evaluating images. Subjective assessment of image quality via a human perception is an essential measure for an image being intelligent. Quality metrics can also track unseen errors as they spread through an image processing flow, and can be employed to assess image processing techniques.

If an image free of distortion is available, then it can be used as a reference to measure the quality of other restored images. For instance, when estimating the quality of compressed images, an uncompressed (original) copy of the image can be utilized as a practical reference. In these situations, the subjective evaluation is directly used to compare the stored image and the reference image. Again, in case of the absence of reference image, mathematical metrics will be deployed. Usually, these metrics estimate quality grades according to anticipated image statistics [13].

FIRST: FULL-REFERENCE QUALITY METRICS

Full-reference algorithms (un-blind measures) compare the restored image versus a perfect reference image with no distortion. These measures may be introduced in the following equations.

A. Mean square error (MSE)

$$MSE_1 = \frac{\sum_i \sum_j (Y(i,j) - \eta(i,j))^2}{M * N} \quad (4)$$

$$MSE_2 = \frac{\sum_i \sum_j (Y(i,j) - \hat{Y}(i,j))^2}{M * N} \quad (5)$$

B. Peak signal-to-noise ratio (PSNR)

$$PSNR(dB) = 10\log_{10}(\frac{255^2}{MSE}) \quad (6)$$

C. Image enhancement factor (IEF)

$$IEF = \frac{\sum_i \sum_j (\eta(i,j) - Y(i,j))^2}{\sum_i \sum_j (\hat{Y}(i,j) - Y(i,j))^2} \quad (7)$$

Y represents the original image, $\hat{Y}$ represents the estimated image, η represents the noisy image, and M x N is the size of the image [1].

D. Performance index (PI)

$$\mathrm{PI} = \frac{\mathrm{MSE2} - \mathrm{MSE1}}{\mathrm{MSE1}} * 100\% \quad (8)$$

The PI is to show the relative amount of increased error or decreased error in the restored image. The percentage performance index can be calculated via multiplying PI by 100. Also, PI is multiplied by a conventional negative (-) sign to show a negative PI value as distortion decreases in the restored image and a positive PI value as distortion increases in the restored image.

SECOND: NON-REFERENCE QUALITY METRICS

No-reference algorithms statistical characteristics of the input image versus a model trained with a large database of naturally obtained images. These no-reference quality assessment methods can include BRISQUE and NIQE models that are expounded as follows [13].

A. BRISQUE

BRISQUE is abbreviation for Blind Reference-less Image Spatial Quality Evaluator. BRISQUE model is trained on a huge data of images with identified distortions. BRISQUE is limited to assessing the image quality with the same type of distortion. BRISQUE is opinion-aware, meaning it is subjective quality scores accompany the training images [13].

B. NIQE

NIQE is abbreviation for *Natural Image Quality Evaluator*. Although NIQE model is trained on a database of pristine images, NIQE can measure the image quality with arbitrary distortion. In the opposite of *BRISQUE*, NIQE is opinion-unaware, and does not employ subjective quality scores. The tradeoff is that the NIQE score of an image might not correlate as well as the BRISQUE score with human perception of quality [13].

IV. RESULTS AND DISCUSSIONS

The processes of intelligent image restoration involves two main types, the filtering process itself and measuring the performance of these filters in detecting informative images. Therefore, PSNR, IEF, MSE, and PI are used in the performance measurement for all filtering techniques, that are investigated against various distorted images, at wide range of 0% – 100% noise density.

The proposed filters are tested using 255X255, 8-bits/pixel standard images such as camera man. The performance of the proposed filters are examined for various levels of noise and compared to each other. These filters are MF, MDF (using 2 windows [3*3] & [5*5]), MXF, MIN and WF. The reference image is distorted by salt and pepper noise of various density percentages ranging from 10 to 90 by an increment of 10. The noisy images are applied to the typical filters for de-noising. The performances of the utilized filters are assessed by the quality metrics discussed earlier. Blind quality measures (BRISQUE and NIQE) that have no image reference are tried too. Their accuracies are displayed and assessed. All filtering and related simulation processes are computed by MATLAB 13 program. The acquired results can be presented as the following.

TABLE I: MSE AND PI VALUES COMPARISON FOR DIFFERENT FILTERS AT VARIOUS NOISE DENSITIES

Noise Density d %	MSE2|					
	MF	MDF	MDF 5*5	Max	Min	WF
10	0.0072	0.0025	0.0047	0.1418	0.1144	0.0134
20	0.0123	0.0041	0.0057	0.2163	0.1792	0.0200
30	0.0193	0.0081	0.0074	0.2695	0.2158	0.0259
40	0.0252	0.0175	0.0095	0.3011	0.2422	0.0324
50	0.0335	0.0362	0.0134	0.3204	0.2572	0.0397
60	0.0424	0.0682	0.0236	0.3310	0.2662	0.0474
70	0.0522	0.1129	0.0525	0.3386	0.2702	0.0589
80	0.0647	0.1684	0.1060	0.3422	0.2740	0.0680
90	0.0750	0.2388	0.2030	0.3441	0.2757	0.0771

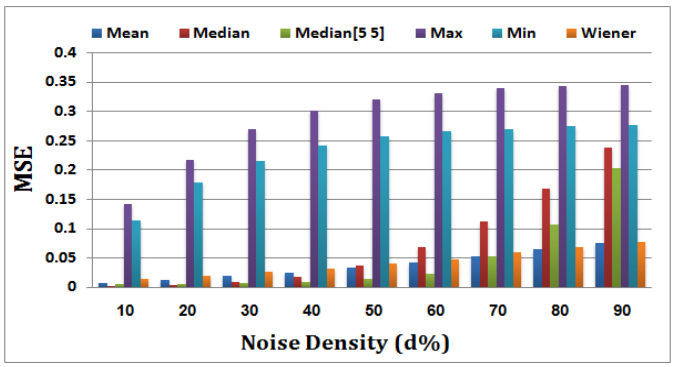


Figure 1: MSE_2 versus values of Salt and Pepper noise density.

TABLE II: IEF VALUES OF DIFFERENT FLTERS AT VARIOUS NOISE DENSITIES

Noise Density d %	PI%					
	MF	MDF	MDF 5*5	Max	Min	WF
10	-76.990	-92.013	-84.790	+353.035	+265.495	-57.188
20	-80.129	-93.376	-90.791	+245.073	+248.627	-67.690
30	-79.323	-91.290	-92.043	+189.785	+132.043	-72.150
40	-79.775	-85.955	-92.376	+141.653	+94.382	-73.997
50	-78.635	-76.795	-91.410	+105.385	+64.872	-74.551
60	-77.290	-63.471	-87.359	+77.290	+42.582	-74.612
70	-76.153	-48.424	-76.016	+54.683	+23.435	-73.093
80	-74.007	-32.342	-57.413	+37.485	+10.084	-72.680
90	-73.243	-14.806	-27.578	+22.761	-1.641	-72.484

TABLE III: PSNR VALUES OF DIFFERENT FILTERS AT VARIOUS NOISE DENSITIES

Noise Density d %	PSNR in dB					
	MF	MDF	MDF5x5	MXF	MNF	WF
10	21.3231	25.9169	23.3056	8.7870	9.4335	18.8535
20	19.1090	23.7997	22.5086	6.6260	7.4880	17.0716
30	17.2983	20.5220	21.3103	5.7564	6.6372	15.7879
40	15.9145	17.5704	20.3802	5.1963	6.1690	14.9550
50	14.8083	14.1760	18.7034	4.9590	5.9138	13.9810
60	13.6292	11.6699	16.3578	4.7960	5.7452	13.2313
70	12.8595	9.4320	12.8504	4.7167	5.6630	12.4644
80	11.9882	7.7186	9.7572	4.6590	5.6251	11.8149
90	11.2592	6.1417	6.8363	4.6350	5.5943	10.9893

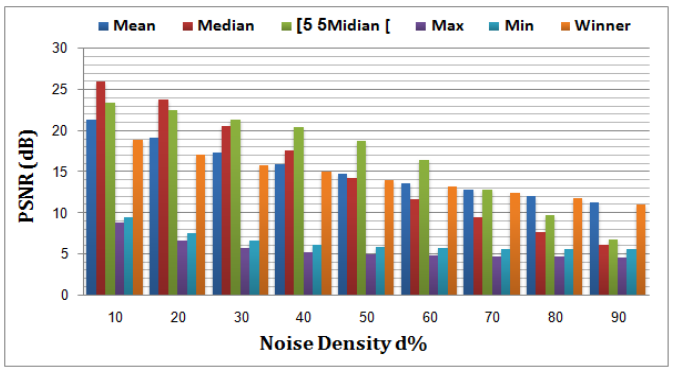


Figure 3: PSNR versus values of Salt and Pepper noise.

TABLE IV: IEF VALUES OF DIFFERENT FILTERS AT VARIOUS NOISE DENSITIES

Noise Density d %	IEF					
	MF	MDF	MDF 5*5	Max	Min	WF
10	4.2781	12.0431	6.5887	0.2272	0.2754	2.3696
20	5.0419	14.9344	11.0619	0.2888	0.3541	3.1701
30	4.9885	10.7879	12.6612	0.3499	0.4310	3.5578
40	4.7593	7.0484	13.3701	0.4122	0.5152	3.8493
50	4.5850	4.0748	11.4759	0.4872	0.6048	3.8802
60	4.3598	2.7452	8.0477	0.5624	0.6989	3.9073
70	4.0318	1.9141	4.2071	0.6461	0.8071	3.8151
80	3.9097	1.4710	2.3546	0.7237	0.9059	3.7444
90	3.7600	1.1599	1.3624	0.8109	1.0193	3.5125

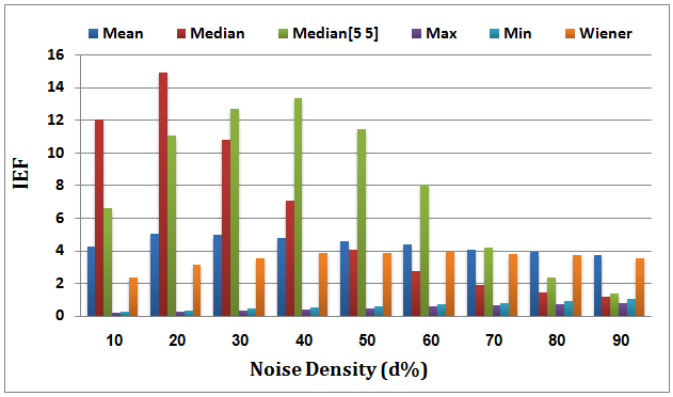


Figure 2: IEF versus values of Salt and Pepper noise.

TABLE V: BRISQUE VALUES OF DIFFERENT FILTERS AT VARIOUS NOISE DENSITIES

Noise Density d %	PRISQUE					
	MF	MDF	MDF 5x5	MXF	MNF	WF
10	37.355	26.072	29.103	43.458	43.458	43.787
30	35.961	28.190	22.456	43.458	43.458	42.992
50	37.887	51.034	20.267	43.502	43.951	43.402
70	41.302	43.979	41.507	47.717	51.981	43.460
90	41.572	43.458	43.458	45.126	44.955	43.405

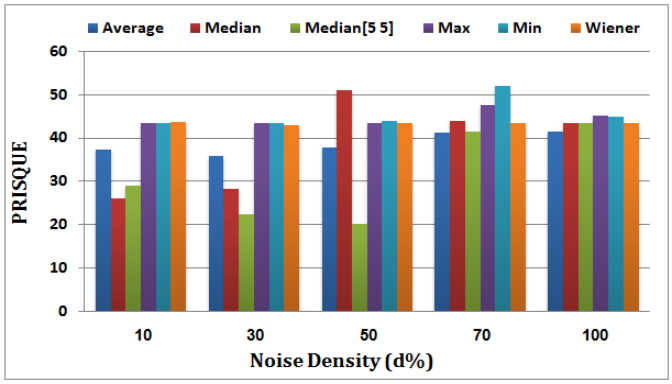


Figure 4: BRISQUE versus values of Salt and Pepper noise.

TABLE VI: NIQE VALUES OF DIFFERENT FILTERS AT VARIOUS NOISE DENSITIES

Noise Density d %	NIQE					
	MF	MDF	MDF 5x5	MXF	MNF	WF
10	6.349	3.857	4.444	61.301	9.4335	20.968
30	8.075	6.679	4.383	42.759	6.6372	16.580
50	10.181	13.299	5.468	40.307	5.9138	12.127
70	11.124	18.524	11.075	24.310	5.6630	12.011
90	11.195	74.018	30.213	24.220	5.5943	10.004

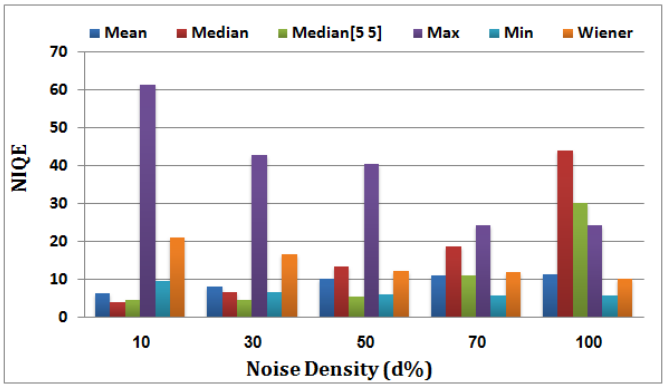
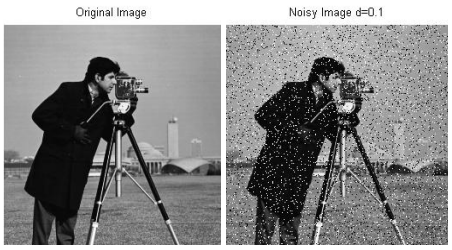


Figure 5: NIQE metric versus values of Salt and Pepper noise.



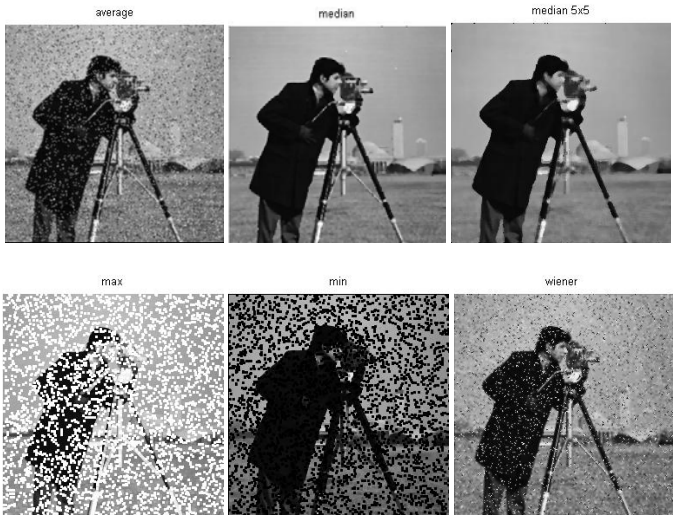


Figure 7: Responses of different filters for gray camera man image. Image restored at 10% noise density.

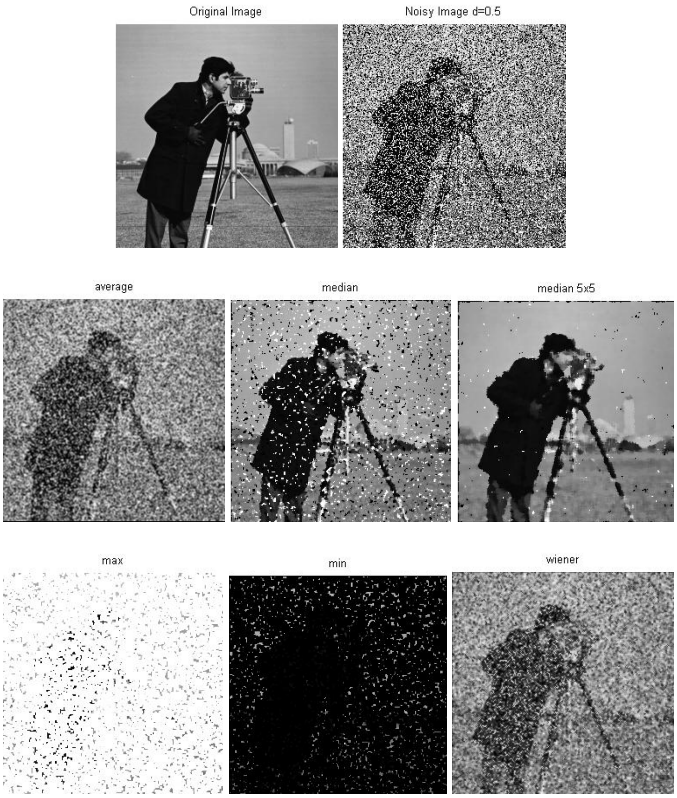


Figure 6: Responses of different filters for gray camera man image. Image restored at 50% noise density.

The results above include the images, tables and graphs that are related to the filters' performance of removing salt and pepper noise with various noise densities. Figures 6 and 7 show the original image, corrupted image and restored images

that are obtained by the various filters for low and medium noise densities respectively.

Tables I, II, III, IV, V, and Figures 1, 2, 3, 4 and 5 represent the measures of MSE, PSNR, IEF, PRIISQUE, and NIQE for the six filters versus the noise density. Median filter [3x3] has the most optimum performance across the noise density of 0% to 30%. On the other hand, Median filter [5x5] has the best performance across the noise density of 30% to 65%.

As for the different filters' performance, MDF (7x7) is able to treat noisy images from 55% to 70% of the noise range. As the MDF window size increases, its performance increases. MDF window of 15x15 is robust enough of covering the noise range up to 90% and increasing PSNR to 14.073. This is the greatest PSNR obtained throughout the whole study. Beyond this size, MDF application is not worth gaining more feasible performance.

Both Wiener and Mean filters demonstrate similar performance that is lower than that of MDF at all noise density values. Max and min filters have the least performance across the noise spectrum of 10% to 100%. In fact, they remove about 50% of the actual noise, but they add different own characteristic noise. It is clear that MXF removes pepper noise, while MNF removes salt noise. Increasing the window size of WF gives reasonable performance improvement, but it is not comparable at all to that of MDF. Certainly, MDF is a robust filter. However, there is no real enhancement in increasing the window size with MX and MN filters as well as with MF filter. These results are confirmed in figures 6 and 7. When the composite filter Min-Max is applied, it still introduces weaker performance.

For the non-reference image measures, BRISQUE model metric provides satisfactory accuracy in measuring filters performance. Certainly, its accuracy cannot beat the referenced measures. In general, there is relative matching in accuracy between reference and non-reference measures in a number of experiments. However, NIQE measure performance is more accurate than BRISQUE. It is obvious that the last two blind metrics have relative match with the referenced ones in terms of the performance accuracy. But, both introduce some exceptional weak cases. These results are demonstrated in figures 4 and 5.

V. CCONCLUSION

The processes of intelligent image de-noising involve two main types, the filtering process itself and the quality metrics that are used to assess the performance of the filters in detecting informative images. Hence, PSNR, IEF, MSE, and PI are to evaluate and qualify all valid filtering techniques, that are investigated against various distorted images, at roughly wide range of 0% – 100% noise density. Accordingly, the main objective of the study to insure valid and qualified quality metrics is in the first place.

Furthermore, the feasibility of the four measurements (MSE, PI, PSNR, IEF) employed to measure the filters' performance shows a high degree of accuracy. This is demonstrated when their performances are checked versus each other and also after compared against the visual assessment of the images. Although the accuracy levels of the blind metrics are still not high enough, their performances are relatively in agreement with the rest of the metrics. However, they can be enhanced through the mechanism of training & learning.

The Median Digital Filter (MDF) has the superior performance from 0% to 70% range of the noise density spectrum. This occurs when the filter windows of [3x3] and [5x5] are employed. MDF [3x3] has the most optimum performance in the range 0% – 30%, while MDF [5x5] has the most optimum performance in the range 30% – 65%. Weiner and mean filters show lower performance and more steady in contrast with other MDF at all noise density range.

Max and Min filters have the least performance, which is up to 10% of the density noise range. Their corresponding restored images at 50% noise density -for example- look like white and black backgrounds respectively.

The final say is that all related autonomous experiments' outcomes of the investigated quality metrics and hence filtering techniques are in good match with the previous published results. Again, all responses of measuring and measured techniques are confirmed that they are in full agreement with the subjective evaluation of the images.

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