Image Denoising using Noise Ratio Estimation, K-means Clustering and Non-local Means based Estimator

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Abstract—One of the key issues in removing random-valued impulse noise from digital images using switching filters is the impulse noise detection. Impulse noise is a random, spiked variation in the brightness of the image. In this paper, a new impulse noise detection algorithm is presented that is based on Noise ratio Estimation and a combination of K-means clustering and Non-Local Means based filter (NEK-NLM). Luo-statistic is employed as a non-local means based estimator. The novelty of this work lies in the introduction of a pre-processing step of noise ratio estimation before noise detection, this estimation allows us to select suitable parameters for the noise detection algorithm. In noise filtering stage, nonlocal-means estimator is applied for restoring noisy pixels to their actual values. Using real world datasets, this paper shows that the impulse noise can be removed effectively. Extensive comparison of simulation results with the already published results show that the proposed method outperforms most of the existing impulse noise removal techniques both in terms of noise detection and image restoration.

Keywords— Image denoising, K-means, non-local means, NEK-NLM, noise filtering, image restoration.

I. INTRODUCTION

An image often gets corrupted by impulse noise while being acquired and transmitted over a channel [1]. Impulse noise not only deteriorates the visual quality of the image, but in practical applications, it degrades the performance of various subsequent image processing operations such as image segmentation and object classification etc. Therefore, to reduce the degradation in performance, denoising and restoration of the image from its corrupted version becomes an integral part of almost all image processing applications.

Highly non-linear nature of impulse noise requires non-linear filtering mechanisms. Standard Median Filter (SMF) is one of the most widely used techniques is standard median (SM) filter [2]. Median filter has gained popularity due to its computational efficiency and robustness to large noise ratios. However, since the median filter is uniformly applied to the whole image, it unnecessarily alters the noise-free pixels too. This causes blurring and may remove desirable fine structures and details from the image. To preserve the details while effectively removing impulse noise, variants of standard median filter such as weighted median filter [3] and center weighted median (CWM) filter [4] have been proposed. All these filters are applied uniformly over the whole image.

The problem is addressed through the space-variant filtering technique which involves switching scheme concept [5]. This technique suggests a two-step filtering mechanism. First is the noise detection stage, in which all the pixels corrupted with the impulse noise are detected. Afterwards, only the noisy pixels are filtered in the effort to restore the original image. In the noise detection stage, thresholding is applied on some locally computed statistics. For example, adaptive center weighted median (ACWM) filter [6] applies thresholding on CWM to mark impulses in the image. Tri-state median (TSM) filter [7] applies thresholding on SM and CWM to detect strong and weak impulses. Various impulse noise filters with improved detection performance have been proposed recently including the multi-state median (MSM) filter [8], peak-and-valley filter [9], [10], signal dependent rank ordered mean (SDROM) filter [11], progressive switching median (PSM) [12] filter, conditional signal adaptive median (CASAM) filter [13], pixel-wise MAD (PWMAD) filter [14], Luo-iterative median filter [15], directional weighted median (DWM) filter, contrast enhancement based filter (CEF) [16] and optimal direction based median (ODM) filter [17]. With the improved noise detection mechanism, these filters aim to target noisy pixels without altering noise-free pixels present in the image. Simple structures of these detectors do not give satisfactory noise detection accuracy and often fine structures present in the image are marked as noise and are filtered out. Also, the noisy pixels in textured regions are sometimes falsely considered as image details and are left unchanged.

The more advanced and improved noise detectors proposed in [18] and [19] are based on rank-ordered statistics. In [18], rank-ordered absolute difference (ROAD) statistics has been proposed for removing the mixture of Gaussian and impulse noise. An improved version of ROAD statistic, called rank-ordered logarithmic difference (ROLD) was presented in [19] which was combined with edge-preserving regularization (EPR) to give ROLD-EPR filter for removing
random-valued impulse noise. In [20], local outlier factor (LOF) has been presented to detect fixed-valued impulse noise. Robust outlyingness ratio (ROR) has been proposed in [21] to identify outlyingness of each pixel. The drawback of these noise detectors is that they use fixed thresholds to identify noisy pixels. Thresholds are determined through extensive experimentation and thus work well for limited type of images. In [22], wavelet transform was used for image denoising employing a thresholding technique based on local contrast and adaptive means. A very comprehensive comparison of different kinds of image denoising techniques has been given in [23]. Here, spatial domain methods, transform based methods and learning based methods are extensively discussed and compared. Another way of impulse noise removal is Standard Median Filter (SMF) [1]. Its main advantage is that its implementation is easy. It has the disadvantage of removing fine details during noise removal process. This incurs the penalty of reduced performance on images with high noise ratios [1]. Genetic Programming (GP) has been applied in [24] for the noise removal. A two stage detector and a two stage estimator methodology is applied in [24]. The technique is named as Universal Impulse Noise Filter based on Genetic Programming (UINFGP).

In this paper, these issues are addressed and a mechanism to measure amount of impulse noise present in an image is introduced. A novel impulse detection algorithm is proposed which is based on Luo-statistic and k-means clustering. The proposed technique is given the name NEK-NLM. In the noise filtering stage, NL-means estimator is applied to restore noisy pixels to their actual values. These results produced by extensive experimentation show that the proposed technique performs better image restoration as compared to existing impulse noise filtering techniques.

The rest of this paper is organized as follows. Section-II describes the proposed impulse filtering mechanism. In Section-III, the experimental results are given for standard test images. Finally, the paper is briefly concluded in Section-IV.

II. THE PROPOSED FILTERING TECHNIQUE (NEK-NLM)

The proposed impulse noise removal method has been structured as a three-step procedure. In the first step, the impulse noise ratio is estimated by comparing corresponding square patches from noisy image and its median image. Subsequently, based on impulse noise ratio, suitable parameters for noise detection algorithm are selected and finally, NL-means is applied for the restoration of the image. Figure 1 depicts the flow of the proposed approach for image restoration.

Figure 1: Block diagram of the proposed image denoising technique (NEK-NLM)

A. Pre-processing Step

Impulse noise may corrupt only a certain portion of image or a certain number of pixels, leaving the remaining pixels intact. Corrupted pixels are significantly different from their neighboring pixels and exhibit no correlation with image content. The image model containing impulse noise with probability $\rho$ (also referred to as noise ratio) can be described as follows:

$$X_{i,j} = \begin{cases} n_{i,j}, & \text{with probability } \rho \\ f_{i,j}, & \text{with probability } 1-\rho \end{cases}$$

(1)

where $X_{i,j}$ and $f_{i,j}$ denote noisy and noise-free pixels respectively at the location $(i, j)$ in the image. Also, $n_{i,j}$ represents a noisy pixel value at the location $(i, j)$. Impulse noise can be classified as fixed-valued impulse noise and random-valued impulse noise (also referred to as uniform impulse noise). For fixed-valued impulse noise, noisy pixels take only extreme values from the dynamic grayscale range of pixel values. However, pixels contaminated by random-valued impulse noise can take any values in the grayscale range.

An estimate of impulse noise ratio in the image can be made if histograms of both noisy and noise-free image are obtained. Since, median filter performs well for smooth and low textured regions in the image, median filtering is applied to the noisy image for estimating the noise-free image. From the filtered image, a square patch of size $64\times64$ having minimum standard deviation is selected. The corresponding patch is also selected from the noisy image. The histograms of these patches are compared to measure extent of impulse noise present in the image. For the Lena image having 30% noise ratio, Figure 2 shows the selected patches and respective histograms from median image, original image and the noisy image.

B. Estimation of Impulse Noise Ratio

Given the noisy and noise-free histograms, following equation is used to obtain the impulse noise ratio $\rho$. 
\[ \text{N-N} \times \rho + \left( \text{N} \times \rho \times \frac{n}{256} \right) = \text{M} \]  

(2)

where \( N \) is the total number of pixels in the selected patch, \( n \) represents number of gray levels present in the noise-free patch, and \( M \) represents the number of pixels in the noisy patch that have gray levels among the set of gray levels present in the noise free patch. Based on the impulse noise ratio, appropriate number of iterations will be decided for impulse noise detector in the following section.

C. The Impulse Noise Detector

The proposed impulse noise detector is an improved variation of noise detector presented in [15], with fixed thresholding replaced by adaptive thresholding mechanism using the K–means clustering algorithm.

1) The Luo-Statistic

Luo-statistic was proposed by W. Luo [15] to separate image details from noisy image and detect the impulses present in the image. Luo-statistic is defined as the absolute deviation of input image from its linear function image. The linear function image is obtained by weighted sum of median and immediate neighbors of the median. The pixel value of linear function image \( F \) at location \((i, j)\) is obtained by using following equation:

\[
F(i,j) = 0.25 \times U(i,j)(4) + 0.50 \times U(i,j)(5) + 0.50 \times U(i,j)(6)
\]

(3)

where \( U(i, j) \) represents array of pixel values sorted in ascending order for a 3x3 size window centered at location \((i, j)\) on the input image. Luo-statistic is defined as absolute deviation of noisy image from its linear function image and is obtained as follows:

\[
\text{Luo}(i,j) = |X(i,j) - F(i,j) |
\]

(4)

Luo-statistic image or simply Luo-image has smooth regions suppressed. Furthermore, it possesses higher amplitude for details and impulses present in the image. After few iterations of Luo-statistic i.e. obtaining Luo image again for the image that is obtained by applying (4), details are also suppressed and only impulses present in the image are left behind.

2) K-means Clustering for Impulse Noise Detection

Details and edges are subtracted from noisy image after few iterations of Luo-statistic and fixed thresholding is applied on the residue image for detection of impulses. The prime issue with this technique is the choice of a fixed threshold; a decision rule which can perform well for images of varying texture and illumination. Usually, fixed thresholds are selected based on extensive experimentation. The problem with this method is the lack of generalization as it works well for limited type of images.

![Figure 2](image)

Figure 2. Selected square patch of size 64x64 with the corresponding histogram, for image Lena (a) 30% corrupted image (b) Median restored image (c) Original image

In this paper, K–means is employed for the classification of image pixels. K-means clustering is applied on Luo-statistic residue image to divide image pixels into two clusters. Pixels belonging to the larger cluster are marked as impulses and those belonging to the other cluster are marked as noise-free pixels. The application of K-means clustering is equivalent to adaptive thresholding with selection of threshold governed by texture and illumination of the respective image.
3) The Detection Algorithm

The whole detection mechanism can be described in algorithmic form as follows:

Step 1. Compute impulse noise ratio for the input image

Step 2. Depending upon impulse noise ratio select \(K_{\text{max}}\), the maximum number of iterations to be performed.

Step 3. Initialise the detection flag matrix \(Flag\) as all zeros, where “1s” and “0s” represent noisy and noise-free pixels respectively.

Step 4. Set \(K = 0\) (\(K\) is number of iterations)

Step 5. Obtain Luo-image \(Luo\) \(c\) (\(c\) is number of iterations of Luo-statistic)

Step 6. Apply \(k\)-means clustering and update the detection flag matrix \(Flag\) to 1 for the pixels mapped to cluster with larger value of cluster centroid.

Step 7. Get the median based restored image \(I\) according to the detection result. If the detection flag is 1, replace the pixel with the median value of its neighbouring pixels.

Step 8. If, \(K < K_{\text{max}}\), \(K = K + 1\) and go to step 5, else the detection stage is complete.

The performance of the proposed impulse noise detector is controlled by the maximum number of iterations for given impulse ratio and the parameter \(c\) i.e. number of iterations of Luo-statistic. The choice of number of iterations is more critical; fewer iterations may leave the impulses present in the image undetected and unaltered, which may give unpleasing effect and degrade the quality of the restored image. However, large number of iterations of the algorithm can cause blurring by filtering out of image details. Optimum values of these parameters are determined empirically. For the given value of impulse noise ratio, performance of noise detector was measured for \(K_{\text{max}}\) in range \([1, 10]\) and \(c\) in range \([1, 10]\) for various test images. Simulation results revealed that the optimum value of \(c\) is 4 irrespective to impulse noise and the number of iterations for approximate impulse noise ratio are listed in Table I.

<table>
<thead>
<tr>
<th>Approximate noise ratio (%)</th>
<th>10</th>
<th>20</th>
<th>30</th>
<th>40</th>
<th>50</th>
<th>60</th>
<th>greater</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of iterations</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>6</td>
<td>8</td>
<td>12</td>
<td>[15-20]</td>
</tr>
</tbody>
</table>

D. NL-means for Impulse Noise Filtering

Originally NL-means was used to denoise images corrupted with Gaussian noise. Extension of NL-means is presented in [21] to remove impulse noise as well. In NL-means, value of each pixel in the noise-free image \(I\) can be represented as weighted sum of all other pixels values in the image. Mathematically, it can be described as follows:

\[
x(i) = \sum_{j \in I} w(i,j) y(j) / \sum_{j \in I} w(i,j)
\]

where \(x(i)\) denotes the estimated value of denoised pixel and \(w(i,j)\) represents the weight of pixel \(y(j)\) involved to estimate the pixel indexed as \(i\). Weights are calculated on the basis of amount of similarity between the neighborhood of contributing pixel and the neighborhood of pixel to be estimated.

\[
w(i,j) = \exp(-\frac{\|y(N_i) - y(N_j)\|^2}{h^2})
\]

where \(y(N_i)\) represents the vector of pixel values of \((2k+1)\times(2k+1)\) size window centered at the pixel indexed \(i\) and \(h\) is the smoothing parameter. The norm used in (6) is Euclidean difference weighted by Gaussian kernel of zero mean and variance \(\alpha\).

Pixels corrupted with impulse noise are significantly different from their neighboring pixels and hence, weights calculated in the presence of impulses would be incorrect. Therefore, weights are calculated from median based restored image with suppressed impulses. The output of the noise detection algorithm is a binary matrix of “1s” and “0s” representing noisy and noise-free pixels, respectively, and the median based restored image. NL-means filter is applied in the filtering stage to improve the quality of restored image.

NL-means is implemented as suggested in [21] with \(h=5\), \(k=3\) and \(W=10\). These are the same parameter as taken in [21]. Searching the whole image for measuring similarity is computationally expensive, thus \((2W+1)\times(2W+1)\) search window is selected around the pixel to be estimated. The proposed algorithm based on new detection mechanism and NL-means estimator has been named as the NEK-NLM filter.

III. EXPERIMENTAL RESULTS

NEK-NLM filter has been evaluated and compared with some of the existing impulse noise filtering techniques. In order to assess the performance of the proposed technique, extensive computer simulations are performed on \(512 \times 512\),
8-bit grayscale standard test images Lena, Bridge, Baboon and Peppers. For comparison with the existing techniques, the average restoration and noise detection results (rounded off to suitable number of significant places) for multiple computer simulations are compared with the results mentioned in [19].

The performance of NEK-NLM filter is also evaluated on the Kodak image dataset [25]. There are a total of 24 images in this dataset and the size of images is 768 x 512 or 512 x 768. The simulations have been carried out for 8-bit grayscale images and impulse noise ranging from 20% to 40%. The results were compared to those obtained from two contemporary techniques: ROR-NLM and ROLD-EPR.

A. Impulse Noise Ratio Estimation Performance

Table 2 gives the impulse noise ratio estimation results for the technique discussed in section-II. Experimental results given in Table II prove that the proposed technique can effectively be applied to measure the extent of impulse noise present in the image.

B. Noise Detection Performance

The detection accuracy is the most important factor for removing impulse noise using switching filters. The performance measure for evaluating noise detector is the detection accuracy i.e. number of false positives (called false-hit) and false negatives (called miss-term) generated by the algorithm. Table III lists the detection results for the proposed technique for Lena image corrupted with various noise ratios, along with some of the existing techniques. The comparison shows that, for each value of impulse noise under consideration, the proposed method gives minimum number of falsely classified pixels. For example, for processing 50% corrupted image, the proposed technique misclassified 18615 pixels, whereas the minimum number of misclassified pixels among other techniques is 22596 by ACWM. In some cases, ACWM generates lesser number of false positives than the proposed technique but it misses a large number of impulses present in the image which severely degrade the restoration performance at the noise filtering stage.

For analysis of the proposed methodology, Figure 3 compares visually the noise detection performance of the proposed technique with ROR-NLM filter, for images Lena and Bridge corrupted with 205 impulse noise. In Figure 3 red dots denote false detected pixels and blue dots denote the mis-detected pixels. It is clear that ROR-NLM filter frequently detects image details and edges as noise, whereas the proposed technique separates image details and impulses more accurately and less often the details are classified as noise.

C. Image Restoration Performance

The overall restoration performance for noise removal is quantitatively measured in terms of peak signal-to-noise ratio (PSNR), which is defined as:

$$PSNR=10\log_{10}\left(\frac{255^2}{\sum_{i=1}^{M} \sum_{j=1}^{N} (x_{ij} - \hat{x}_{ij})^2 / MN}\right)$$

where $I_{ij}$ and $x_{ij}$ denote the pixel values of the original and restored images at the location $(i, j)$, respectively and the image size is $M \times N$. In Table IV, the restoration results of the proposed technique are listed on four standard test images corrupted with impulse noise ranging from 30 – 50%, along with the restoration results for some of the existing techniques [19].

Figure 3: Comparison of noise detection for 10% corrupted *Lena* and *Bridge* images (a) NEK-NLM (b) ROR-NLM

Table III
Comparison of noise detection for Lena image corrupted with various noise ratios

<table>
<thead>
<tr>
<th>Noise Ratio</th>
<th>20%</th>
<th>30%</th>
<th>40%</th>
<th>50%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Filter</td>
<td>miss</td>
<td>false-hit</td>
<td>total</td>
<td>miss</td>
</tr>
<tr>
<td>SWM</td>
<td>8836</td>
<td>3648</td>
<td>12484</td>
<td>12644</td>
</tr>
<tr>
<td>TRI</td>
<td>8995</td>
<td>2841</td>
<td>11836</td>
<td>13667</td>
</tr>
<tr>
<td>MSM</td>
<td>8598</td>
<td>3162</td>
<td>11760</td>
<td>12973</td>
</tr>
<tr>
<td>ACWM</td>
<td>6754</td>
<td>1523</td>
<td>8277</td>
<td>10344</td>
</tr>
<tr>
<td>Luo-IMF</td>
<td>8467</td>
<td>1225</td>
<td>9692</td>
<td>12932</td>
</tr>
<tr>
<td>DWM</td>
<td>8530</td>
<td>4497</td>
<td>13027</td>
<td>10586</td>
</tr>
<tr>
<td>ROLD-EPR</td>
<td>9158</td>
<td>4321</td>
<td>13670</td>
<td>11133</td>
</tr>
<tr>
<td>ROR-NLM</td>
<td>5863</td>
<td>5643</td>
<td>11506</td>
<td>9064</td>
</tr>
<tr>
<td>NEK-NLM</td>
<td>6684</td>
<td>1106</td>
<td>7790</td>
<td>8431</td>
</tr>
</tbody>
</table>

Table IV
Comparison of image restoration in PSNR (dB) for images corrupted with various noise ratios

<table>
<thead>
<tr>
<th>Filter</th>
<th>Bridge</th>
<th>Baboon</th>
<th>Lena</th>
<th>Peppers</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>30%</td>
<td>40%</td>
<td>50%</td>
<td>30%</td>
</tr>
<tr>
<td>SWM</td>
<td>23.85</td>
<td>22.64</td>
<td>20.98</td>
<td>21.50</td>
</tr>
<tr>
<td>TRI</td>
<td>25.10</td>
<td>23.65</td>
<td>21.71</td>
<td>22.72</td>
</tr>
<tr>
<td>MSM</td>
<td>25.30</td>
<td>23.54</td>
<td>21.33</td>
<td>23.02</td>
</tr>
<tr>
<td>ACWM</td>
<td>25.22</td>
<td>23.76</td>
<td>22.18</td>
<td>22.74</td>
</tr>
<tr>
<td>Luo-IMF</td>
<td>25.40</td>
<td>23.98</td>
<td>22.313</td>
<td>22.90</td>
</tr>
<tr>
<td>DWM</td>
<td>8530</td>
<td>4497</td>
<td>13027</td>
<td>10586</td>
</tr>
<tr>
<td>ROLD-EPR</td>
<td>25.76</td>
<td>24.70</td>
<td>23.67</td>
<td>22.98</td>
</tr>
<tr>
<td>SMF</td>
<td>23.24</td>
<td>21.11</td>
<td>19.01</td>
<td>21.14</td>
</tr>
<tr>
<td>NEK-NLM</td>
<td>25.47</td>
<td>24.22</td>
<td>22.98</td>
<td>22.80</td>
</tr>
</tbody>
</table>

(a) 
(b)

Figure 4. Comparison of image restoration for 50% corrupted images Lena and Bridge (a) Original images (b) Noisy images (c) Restored images for ROR-NLM (PSNR, for Lena 26.65 and for Bridge 21.07) (d) Restored images for NEK-NLM (PSNR, for Lena 22.01 and for Bridge 28.57)

It is observed from Table IV that the proposed technique outperforms most of the existing random-valued impulse noise removal techniques. Qualitative comparison of the proposed technique is presented in Figure 4 for test images Lena and Bridge corrupted with 50% impulse noise ratio and restored with the proposed technique and ROR-NLM filter. The quality of image restored using the proposed technique is visibly better because of its more accurate noise detection mechanism. The results clearly show that the proposed technique removes impulse noise and preserves the image details more effectively.

D. Performance Evaluation on Kodak dataset

The performance of the proposed technique was evaluated for the Kodak image suite as well. The results of the simulations of the proposed technique are compared with two of the contemporary techniques i.e. ROR-NLM and ROLD-EPR. The impulse noise level was varied from 20% to 40%.

Figure 5 shows the results obtained by using the proposed image restoration technique NEK-NLM. Figure 5(a) shows three of the original images of Kodak dataset. Introducing 40% noise ratio results in the corrupted images shown in Figure 5(b). The restored images obtained after NEK-NLM filtering is applied on the noisy images are shown in Figure 5(c). It is evident from the figure that the performance of the proposed filtering technique is satisfactory.
Table V presents the comparison based on the noise detection performance measures, i.e., False-hit and Miss-term. PSNR values are also compared which signifies the image restoration performance measure. The noise ratio used was 20%. From this comparison, it is clear that on standard Kodak image dataset, the performance of the proposed technique is superior to the other contemporary filtering techniques. PSNR is high for all the images filtered with NEK-NLM technique.

Table V
Comparison of noise detection and image restoration for all images of Kodak dataset with a noise ratio of 20%.

<table>
<thead>
<tr>
<th>Image</th>
<th>False-hit</th>
<th>Miss</th>
<th>PSNR (dB)</th>
<th>False-hit</th>
<th>Miss</th>
<th>PSNR (dB)</th>
<th>False-hit</th>
<th>Miss</th>
<th>PSNR (dB)</th>
</tr>
</thead>
<tbody>
<tr>
<td>im01</td>
<td>28943</td>
<td>14431</td>
<td>24.75407</td>
<td>55702</td>
<td>11770</td>
<td>22.71359</td>
<td>6935</td>
<td>76450</td>
<td>23.98082</td>
</tr>
<tr>
<td>im02</td>
<td>16065</td>
<td>5673</td>
<td>33.33486</td>
<td>12791</td>
<td>8424</td>
<td>31.68461</td>
<td>2148</td>
<td>77140</td>
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</tr>
<tr>
<td>im03</td>
<td>8878</td>
<td>5682</td>
<td>34.51357</td>
<td>10687</td>
<td>7141</td>
<td>32.56445</td>
<td>1972</td>
<td>77157</td>
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</tr>
<tr>
<td>im04</td>
<td>14228</td>
<td>6573</td>
<td>32.91456</td>
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<td>43207</td>
<td>12046</td>
<td>23.07893</td>
<td>8162</td>
<td>76110</td>
<td>31.14722</td>
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<tr>
<td>im06</td>
<td>21713</td>
<td>11665</td>
<td>26.72591</td>
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<td>10157</td>
<td>24.81389</td>
<td>5323</td>
<td>76794</td>
<td>25.92228</td>
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<tr>
<td>im07</td>
<td>9695</td>
<td>6484</td>
<td>32.59554</td>
<td>10806</td>
<td>8750</td>
<td>30.4396</td>
<td>3892</td>
<td>76697</td>
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<tr>
<td>im08</td>
<td>21669</td>
<td>18920</td>
<td>22.16176</td>
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<td>20.06725</td>
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<td>3895</td>
<td>77103</td>
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</tbody>
</table>

Figure 6 shows the graphs of PSNR values for Kodak image dataset with 20% noise ratio. It is obvious from Figure 5 that the proposed filtering technique, i.e., NEK-NLM outperforms ROR-NLM and ROLD-EPR filtering techniques. PSNR for NEK-NLM is superior as compared to the other two contemporary techniques for all of the images in the Kodak image dataset.

Figure 6. Comparison of PSNR of different filtering methods for all the Kodak images for a noise ratio of 20%

Table VI shows the comparison of the noise detection performance measures and PSNR values. The noise ratio was kept 30%. It is observed, that the proposed filtering technique provides high PSNR compared to ROR-NLM and ROLD-EPR.

Table VI
Comparison of noise detection and image restoration for all images of Kodak dataset with a noise ratio of 30%.

<table>
<thead>
<tr>
<th>Image</th>
<th>False-hit</th>
<th>Miss</th>
<th>PSNR (dB)</th>
<th>False-hit</th>
<th>Miss</th>
<th>PSNR (dB)</th>
<th>False-hit</th>
<th>Miss</th>
<th>PSNR (dB)</th>
</tr>
</thead>
<tbody>
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<td>24.17067</td>
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<td>13625</td>
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<td>12088</td>
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<td>59091</td>
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</table>
Figure 7 shows the plots for PSNR values on Kodak image dataset with 30% noise ratio for NEK-NLM, ROR-NLM and ROLD-EPR. Again, PSNR is highest for all images with NEK-NLM technique, whereas, ROR-NLM provides minimum PSNR. There is an overlap between some of the PSNR values for ROR-NLM and ROLD-EPR techniques.

The comparison of noise detection performance measures and PSNR values for 40% noise ratio is presented in Table VII. Although for most of the images, PSNR is high with NEK-NLM but there are some cases for which the other two techniques give better results.

Table VII
Comparison of noise detection and image restoration for all images of Kodak dataset with a noise ratio of 40%.

<table>
<thead>
<tr>
<th>Filter</th>
<th>NEK-NLM</th>
<th>ROR-NLM</th>
<th>ROLD-EPR</th>
</tr>
</thead>
<tbody>
<tr>
<td>Image</td>
<td>False-hit</td>
<td>Miss</td>
<td>PSNR (dB)</td>
</tr>
<tr>
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<td>12039</td>
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<td>23.07359</td>
</tr>
<tr>
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<tr>
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<tr>
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<tr>
<td>im05</td>
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<td>24.68579</td>
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Table:

<table>
<thead>
<tr>
<th>Image</th>
<th>NEK-NLM</th>
<th>ROR-NLM</th>
<th>ROLD-EPR</th>
</tr>
</thead>
<tbody>
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<tr>
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</table>

Figure 8 shows the curves of PSNR for Kodak image dataset with a noise ratio of 40%. At 40% noise ratio, the performance of NEK-NLM, ROR-NLM and ROLD-EPR is comparable.

Although the proposed technique has proved to be successful, there is still a room for improvement. It is clear from the results on Kodak dataset that the proposed technique is superior to the contemporary techniques when noise ratio is below 40%. Hence the important point for the future research is how to improve the estimation and hence the restoration performance when impulse noise ratio is even higher. In the light of the proposed technique, following areas can be improved and addressed in future studies.

1. Instead of selecting a patch size of 64x64 for the histogram comparison, an adaptive methodology can be employed. In such a methodology, patch size shall be selected based on the noise in the particular image as well as the size of the image.

2. For the noise ratio greater than 40%, median filter introduces blurring in the image. Hence instead of using only median filtering for all noise ratios, other filtering methods can also be tested e.g. center-weighted median filtering.
IV. CONCLUSION

This paper proposes a novel two stage impulse noise filter called NEK-NLM. The main novelty of the proposed filter lies in the noise ratio estimation before noise detection. It utilizes a combination of Luo-statistic and K-means clustering algorithm to obtain an impulse detector, which adaptively adjusts thresholds for noise detection, for images of varying texture and brightness. The use of NL-means estimator at filtering stage significantly improves the quality of the restored image. The empirical results shown, advocate the usefulness of the proposed filter for denoising the noisy images. The average PSNR for Kodak dataset with 20% noise ratio is 29.16 dB for NEK-NLM, 28.13 dB for ROLD-EPR and 27.35 dB for ROR-NLM. Similarly the average PSNR for 30% noise ratio is 28.45 dB, 27.13 dB and 26.83 dB for NEK-NLM, ROLD-EPR and ROR-NLM respectively. Average PSNR for 40% noise ratio is 26.47 dB, 26.37 dB and 26.13 dB for NEK-NLM, ROLD-EPR and ROR-NLM respectively. Most of the images in real world are corrupted by impulse noise that may range from 2-3% to 30-40% noise ratio. The main aim of the developed technique was to provide superior results in this range of impulse ratio. So that the technique can be applied to the real world images, even for the impulse noise ratio as high as 40%. From the aforementioned results, it is concluded that the noise removal via NEK-NLM is superior to other contemporary techniques. The proposed technique can be applied to different modalities after extensive simulations and hence adjustment of different parameters according to the modality. In the future, the proposed technique can be improved by employing Deep Neural Networks for the restoration stage.

REFERENCES