Efficient adaptive fuzzy-based switching weighted average filter for the restoration of impulse corrupted digital images

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Abstract: This study proposes a new fuzzy adaptive filter for the restoration of impulse corrupted digital images. The proposed filter incorporates fuzzy functions to model the uncertainties, while detecting and correcting impulses. The traditional, SMALL fuzzy function is used to identify the non-impulsive nature of the detected corrupted pixels in the initial step. For the better restoration of detected impulse pixels, a modified version of Gaussian function is utilised to determine the similarity among the detected uncorrupted pixels. The proposed correction scheme provides more weight to the uncorrupted pixels that show much similarity with other uncorrupted pixels in the window while replacing impulses. The proposed filter adapts to various noisy and image conditions and is capable of suppressing noise while preserving image details. The experimental results in terms of subjective and objective metrics favour the proposed algorithm than many other prominent filters in literature.

1 Introduction

Impulse noise affects digital images when they are imaged by erroneous sensors or when they are transmitted through faulty communication channels. Salt and pepper is a type of impulse noise which corrupts randomly selected pixels of digital image into a very large value as positive impulse or a very small value as negative impulse [1]. Since this noise affects the true content of the image, the challenge in the image processing domain is to effectively reduce the effect of impulse noise while preserving the finer image details. Median filters are the popular non-linear filters extensively applied to eliminate salt and pepper noise because of its computational efficiency and simplicity. The Median filter uniformly replaces the gray values of all pixels in the image irrespective of whether they are corrupted or not by the median of respective pixels in the static neighbourhood and provides good noise suppression since the noise candidates falls in extreme ranges of a sorted array while determining median. The position-invariant nature of Median filter and its variants [1–3] during restoration consumes image details while removing impulses. Moreover, it does not address any corruption check for the determined median before replacing the pixels. These limitations met by median filter are addressed by many next generation filters like noise adaptive switching median filter (NASMF) [4], boundary discriminative noise detection filter (BDND) filter [5], adaptive switching median filter (ASMF) [6] by introducing decision/switching schemes during the filtering phase.

As an extension to NASMF, the noise adaptive fuzzy switching median filter (NAFSM) [7] utilises the histogram of the corrupted image to identify noisy pixels and later uses fuzzy reasoning to restore the impulses that are detected. However, the noise detection stage is very simple and the possibility of misclassification of uncorrupted pixels as impulses is more. Hsien et al. [8] proposed the turbulent particle swarm optimisation (PSO) based fuzzy image filter (TPF) by incorporating fuzzy turbulent PSO, but the filter is computationally complex because of the numerous iterations performed by the optimisation. Fitri et al. [9] proposed fuzzy mean linear aliasing window kernel (FMLAWK) filter comprising of two filters wherein first filter detects the impulses and approximate initial result by replacing the impulses with the mean of uncorrupted pixels from a prefixed window, while the second filter aliases the approximation image by decomposing the pixels in 3 × 3 window centred at each corrupted pixels and then by interpolating them to give singular value. However, the image goes over blurred because of the numerous interpolations. Yildirim and Basturk [10] proposed a type-2 fuzzy logic-based filter by incorporating many directional masks to preserve the edge details. Although the filter performs well for images corrupted with smaller quantum of impulse noise, fails to perform better in cases where
image goes highly corrupted. The filter proposed by Xu et al. [11] use an $S$ function to fuzzify the amount of corruption of individual pixels. However, the filter could not provide ample restoration since there is no adaptation in the window size. Numerous other filters [14–21] also introduced with different switching and optimisation schemes by meeting some requirements of impulse noise filtering but failed to simultaneously meet on other vital requirements like the computational efficiency, misclassification of pixels, maintaining fidelity in restored outputs and so on. 

This paper proposes a new adaptive fuzzy-based switching weighted average (AFSWA) filter for the detection and filtering of salt and pepper impulse noise. The proposed filter also concentrates to maintain fidelity in the restored images. This paper is organised in six sections. Section 2 introduces the new fuzzy-based impulse filter; Section 3 provides the experimental methodology used for comparing the performance of the proposed filter. The comparative analysis on the subjective and objective metrics of the proposed filter with other prominent filters is presented in Section 4. Section 5 and Section 6, respectively, makes the conclusion and future scope of the work.

2 AFSWA filter

The proposed AFSWA filter works in two distinct stages of impulse detection and impulse correction.

2.1 Impulse detection stage

First, a fuzzy flag image $f$ is created to indicate the amount of corruption of each pixel in the given corrupted image of same size as the input image $X$ of size $M \times N$ to be filtered where $f_{i}$ and $X_{i}$ respectively, denote the flag value and pixel value at position $i = (i_1, i_2)$. We set $f_{i} = 0$ to indicate the pixel value at spatial position $i$ to be an impulse and $f_{i} = 1$ when the pixel value at $i$ is not impulse. Initially this fuzzy flag image, $f$, is set to ‘0’ at all its spatial locations assuming that all the pixels of the image, $X$ are fully corrupted. $f_{i}$ is the fuzzy membership value allotted to the pixel at position $i$ to indicate the impulsive or uncorrupted nature of the pixel. The value of $f_{i}$ ranging from 0 to 1 is the degree of the purity of the pixel that varies from impulsive to uncorrupted. An impulse corrupted pixel has characteristics very similar to that of an edge pixel. So, $f_{i}$ is determined through the following steps by using the fuzzy rules defined on minimum directional differences. The impulse detection scheme can be tracked through the following steps:

**Step 1:** The set of non-impulsive pixels, $\psi$ is initialised to $\psi = \phi$ and the window size, $W$ for analysis of pixels is identified. A larger window size is better to decide the purity status of a pixel corrupted with salt and pepper noise, but we set $W = 3$ since it reduces the computational complexity and we have additional refinement step to reduces the misclassifications of pixels.

**Step 2:** The set of spatial positions within a square window $W \times W$, centred at each pixel position, $i = (i_1, i_2)$, is defined by the set, $\Omega^W_i$ as

$$\Omega^W_i = \{j = (j_1, j_2) | j_1 - (W - 1)/2 \leq j_1 \leq i_1 + (W - 1)/2, j_2 - (W - 1)/2 \leq j_2 \leq i_2 + (W - 1)/2\}$$

(1)

Here, $W$ indicates the size of the local neighbourhood window under consideration. The phase begins by analysing the pixel-wise characteristics of the corrupted image, $X$ in the local neighbourhood, $W \times W$.

**Step 3:** We check the purity status of $X_i$ by comparing it with the minimum, $M_1$ and maximum, $M_2$ as

$$f_{i=(i_1, i_2)} = \begin{cases} 1 & \text{if } M_1 < X_i < M_2 \\ f_{i} & \text{otherwise} \end{cases}$$

(2)

where

$$M_1 = \min \{X_{j}/j \in \Omega^W_i\}$$

(3)

$$M_2 = \max \{X_{j}/j \in \Omega^W_i\}$$

(4)

**Step 4:** We fuzzify the purity status of $X_i$ when $X_i$ is found not to lie strictly in between $M_1$ and $M_2$ since edge pixels are also having similar properties. To estimate the amount of corruption of detected corrupted pixels, the uncorrupted pixels in the neighbourhood around $X_i$ are caught in the impulse-free pixel set, $\psi$, that is,

$$\psi = \{X_{j}/j \in \Omega^W_i \text{ and } M_1 \leq X_j \leq M_2\}$$

(5)

**Step 5:** If the cardinality of uncorrupted pixels, $\psi$ is greater than a predefined threshold, $T_1$, it is easy to find whether the current pixel under consideration is an edge pixel similar to the noise. Hence, we find the directional distances, $d_k$ in each direction, $k$ as defined in Fig. 1 as (see (6))

![Fig. 1](https://www.ietdl.org/)  

**Fig. 1** Directional weights

$$d^k_i = \frac{\sum_{l_1=-2}^{L_1} \sum_{l_2=-2}^{L_2} w^k (3 + l_1, 3 + l_2) \left | X(i_1 + l_1, l_2) - X(i_1 + l_1, l_2 + l_2) \right |}{\sum_{l_1=-2}^{L_1} \sum_{l_2=-2}^{L_2} w^k (3 + l_1, 3 + l_2)}$$

(6)
2.2 Fuzzy similarity among uncorrupted pixels

We determine the fuzzy similarity of detected uncorrupted pixels with other uncorrupted pixels in the analysis window in order to make efficient replacement of detected corrupted pixels. This can be achieved if there is sufficient number of uncorrupted pixels in the neighbourhood. We determine the set of uncorrupted pixels in the correction window, $W_s$ as

$$\psi = \left\{ \frac{Z}{i} \mid j \in \Omega_i^{W_s} \text{ and } f_j > T_2 \right\}$$

where

$$\Omega_i^{W_s} = \{ j = (j_1, j_2)/i_1 - (W_s - 1)/2 \leq j_1 \leq i_1 + (W_s - 1)/2 \}
\{ i_2 - (W_s - 1)/2 \leq j_2 \leq i_2 + (W_s - 1)/2 \}$$

We set the analysis window, $W_s = 3$ since smaller window gives much correlation among pixels. The increase in the cardinality of $\psi$ indicates that there is sufficient number of uncorrupted pixels to determine fuzzy similarity among the pixels and hence we determine the fuzzy similarity of the pixel under consideration with other pixels by incorporating the modified Gaussian function as shown in Fig. 3. It can be mathematically defined by

$$\mu_k = \exp \left( -\frac{(\psi_\beta)^2}{(c + 2\sigma)^2} \right), \quad \forall \psi_k \in \psi$$

Here, $c$ is a constant and $\sigma$ is the standard deviation of $\psi$. For our algorithm we use $c = 0.001$ to avoid divide by zero error.

In order to identify the top similar membership values, we sort $\mu_k$ in descending to obtain $S\mu_k$ such that

$$S\mu = \text{sort}(\mu)$$

such that

$$S\mu = \{ S\mu_1 \leq S\mu_2 \leq \cdots \leq S\mu_k \}$$

The final fuzzy similarity membership function is determined as

$$f_i^S = \begin{cases} \sum_{i=1}^{n_1} S\mu_{i_j} & \text{if } k > T_3 \\ f_i & \text{Otherwise} \end{cases}$$

Here $n_1$ is a positive integer less than $k$ and $T_3$ is a threshold.

2.3 Impulse correction stage

The correction algorithm starts by taking the inputs of the flag image, $f_i$ fuzzy similarity image, $f_i^S$ and the input image, $Z$. The algorithm process each pixel in the image at position $i = (i_1, i_2)$ such that $(i_1, i_2) \in \text{Domain}(X)$ and can be tracked through the following steps.

Step 1: If the flag value, $f_i$ of the pixel $X_i$ is greater than a threshold $T_2$, it is retained in the restored image, $U$ since the membership of $X_i$ is more towards non-corruption. Thus,

$$U_i = X_i$$

Now the algorithm is continued from step 7.

Step 2: Otherwise, if the flag value, $f_i$ is less than threshold $T_2$, the pixel position at $i'$ is decided to be impulse corrupted and so we start the process by initialising the uncorrupted pixel set, $\psi = \phi$ and the initial correction window, $W_c = 3$.

Step 3: The pixel positions of the pixels within the impulse correction window, $W_C$, centred at the position $i'$, are caught into the set $\Omega_i^{W_C}$

$$\Omega_i^{W_C} = \{ j = (j_1, j_2)/i_1 - (W_c - 1)/2 \leq j_1 \leq i_1 + (W_c - 1)/2 \}
\{ i_2 - (W_c - 1)/2 \leq j_2 \leq i_2 + (W_c - 1)/2 \}$$

Fig. 2  Membership functions for SMALL.

Fig. 3 Modified Gaussian function for fuzzy similarity among uncorrupted pixels.

Step 6: Lower values in any directional distances indicate the presence of an edge in the corresponding direction passing through the pixel under consideration. In order to model the uncertainty of the corruption status of these pixels, a fuzzy membership function SMALL is defined as in Fig. 2.

Accordingly, we form the membership of purity as

$$f_i = \text{SMALL}(\min(a^k_i)) \quad \forall k = 1, 2 \ldots 4$$

Step 7: We move to the next pixel for processing and repeat step 1 through step 7 until all pixels in the image are processed.

Since we incorporated fuzziness by considering directional distances, the chances of escaping of edge pixels similar to that of impulse counterparts from wrongly detected as impulses are more.
Step 4: The uncorrupted pixels identified by \( \Omega^{WC}_{i} \) together with fuzzy similarity measure, \( f^3 \) are caught into the ordered set \( F_\psi \) in accordance to the flag values assigned to them in the flag image, \( f \) as

\[
F_\psi = \left\{ \left( X_j, f_j^3 \right) / j \in \Omega^{WC}_{i} \text{ and } f_j > T_2 \right\}
\]

and

\[
l_2 = \text{Cardinality } (F_\psi)
\]

Step 5: if \( l_2 \neq 0 \) we replace the corrupted pixel by weighted mean of \( F_\psi \) as

\[
U_i = \frac{\sum_{(x_1, y_1) \in F_\psi} x_1 \times y_1}{\sum_{(x_1, y_1) \in F_\psi} y_1}
\]

Here \( U_i \) is the signal restored at the impulse corrupted position, \( i \). The algorithm is now continued from step 7.

Step 6: Otherwise if \( l_2 = 0 \) then it indicates that no pixel in the current window is uncorrupted and hence we increase the correction window size \( W_C \) to \( W_C + 2 \) and process from step 3.

Step 7: Move to the next pixel for processing from step 1.

After the impulse correction stage, the grey levels in the impulse corrupted pixel positions are replaced by signals selected from the most appropriate neighbourhood and are similar to the original signal of that position.

3 Experimental methodology

The proposed AFSWA filter is tested on a variety of digital images of which the 8 bit Lena, Boats and Allen images of size \( 512 \times 512 \) are used in this paper for objective and subjective comparisons with the results of top-ranking other impulse filters: the ROM [12], the simple median filter [1], the centre weighted median filter (CWMF) [2], morphological median filter (MMF) [3], progressive switching median filter (PSMF) [13], long range correlation filter (LRCF) [14], BDND [5], NAFSM filter [7] and FMLAWK filter [9]. The objective metrics used for analysing the improved performance of the proposed impulse detection and correction stages of AFSWA are the miss-detection (MD), false alarm (FA), peak signal-to-noise ratio (PSNR) and the mean absolute error (MAE). MD of an impulse detection algorithm is the total number of occurrences involving the identification of an impulse as a signal. Conversely, FA is the total number of occurrences when uncorrupted pixels are misclassified as noise. A well designed impulse detection algorithm which differentiates high-frequency signal details and the equivalent impulses produces less number of MDs and FA. The MAE is the

![Fig. 4 Outputs of NAFSM, FMLAWK and the proposed AFSWA of Lena image, respectively, from the second column against varied impulse noise levels [(a) 10%, (e) 50%, (i) 90%]](image_url)
average of the absolute differences between the input and output image pixels. The MAE between the restored image, \( U \) and the original noise-free image, \( X \), both of sizes \( M \times N \) is

\[
\text{MAE} = \frac{1}{MN} \sum_{x=1}^{M} \sum_{y=1}^{N} |U(x, y) - X(x, y)|
\]  

A detail preserving impulse filtering algorithm generates outputs with high fidelity and hence the restored outputs will be similar to the original noise-free digital image with minimal mean-square error (MSE). PSNR is the measure for determining the quality of the restored output and is the ratio of the maximum signal intensity of the digital image to the power of noise which affects the fidelity of signal. Thus PSNR is defined as

\[
\text{PSNR} = 10 \log_{10} \left( \frac{(2^n - 1)^2}{\text{MSE}} \right) \text{ dB}
\]

The percentage of not detected edges, \( \xi_1 \), is the percentage of edges present in the edge image of the impulse-free image but not present in the edge image of the impulse filter’s output. The percentage of wrongly detected edges, \( \xi_2 \), is the percentage of edges that are present in the edge image of the restored output but are not present in the edge image of the impulse-free image. Canny edge detection algorithm is used for determining \( \xi_1 \) and \( \xi_2 \).

4 Experimental results and analysis

The details-preserving aspect of the proposed filter together with other top-ranking filters is analysed through the visual comparison of the restored outputs in Figs. 4–6 and also emphasised numerically by calculating how well the edges are preserved using the edge details metrics: the percentage of not detected edges, \( \xi_1 \), and the percentage of wrongly detected edges, \( \xi_2 \). The subjective comparison made in Figs. 4 and 5, respectively, on images Lena and Allen for

\[
\text{MSE} = \frac{1}{MN} \sum_{x=1}^{M} \sum_{y=1}^{N} |U(x, y) - X(x, y)|^2
\]  

Here \( 2^n - 1 \) correspond to the maximum grey level in the digital image that represents a pixel with \( n \) bits and MSE corresponds to the average of the square of the errors between the signal forecasts and the true signals.

Fig. 5 Outputs of NAFSM, FMLAWK and the proposed AFSWA filter of Allen image, respectively, from the second column against varied impulse noise levels [(a) 10%, (e) 50%, (i) 90%]
4.1 Parameter settings and analysis

The values of the filtering parameters used in the proposed algorithm plays an important role in the behaviour of the filter. Behaviour of thresholds $T_1$ depends up on the noise levels and can be described in following four cases as can be viewed from Table 7 that shows the misclassifications of pixels for various $T_1$ against different noise ratios. Note that the total misclassifications used in Table 8 are calculated as the sum of MD and FA.

**Case 1:** If the noise level is low and the threshold, $T_1$ is low, there will be many uncorrupted pixels in the window; all the pixels will participate in the refinement. Some rare cases where there will not be sufficient uncorrupted pixels in the current window may yield for wrongly detecting impulses as correct pixels.

**Case 2:** If the noise is low and the threshold, $T_1$ is high, there will be many uncorrupted pixels in the window, these pixels cannot participate in the refinement. This will result in wrongly detecting correct pixels as impulses.

**Case 3:** If the noise is high and the threshold, $T_1$ is low, there will be many uncorrupted pixels in the window; all

### Table 1: Objective metrics produced by different filters for Lena corrupted by 10% impulse noise

<table>
<thead>
<tr>
<th>Filters</th>
<th>PSNR</th>
<th>MAE</th>
<th>$\xi_1$</th>
<th>$\xi_2$</th>
<th>MD</th>
<th>FA</th>
</tr>
</thead>
<tbody>
<tr>
<td>ROM 3*3</td>
<td>32.634</td>
<td>3.183</td>
<td>2.358</td>
<td>1.704</td>
<td>20</td>
<td>6269</td>
</tr>
<tr>
<td>Median 3*3</td>
<td>33.712</td>
<td>2.760</td>
<td>2.144</td>
<td>1.425</td>
<td>16</td>
<td>0492</td>
</tr>
<tr>
<td>CWMF 3*3</td>
<td>35.577</td>
<td>1.749</td>
<td>1.609</td>
<td>1.413</td>
<td>93</td>
<td>308</td>
</tr>
<tr>
<td>MMF 3*3</td>
<td>30.252</td>
<td>4.269</td>
<td>4.276</td>
<td>3.100</td>
<td>217</td>
<td>765</td>
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<tr>
<td>PSMF</td>
<td>33.961</td>
<td>0.794</td>
<td>0.936</td>
<td>1.320</td>
<td>11</td>
<td>76</td>
</tr>
<tr>
<td>LRCF</td>
<td>38.799</td>
<td>0.493</td>
<td>0.839</td>
<td>0.674</td>
<td>47</td>
<td>58</td>
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<tr>
<td>BDND</td>
<td>41.152</td>
<td>0.348</td>
<td>0.619</td>
<td>0.564</td>
<td>0</td>
<td>3</td>
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<tr>
<td>NAFSM</td>
<td>41.860</td>
<td>0.432</td>
<td>0.730</td>
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<td>0</td>
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<tr>
<td>FMLAWK</td>
<td>42.331</td>
<td>0.380</td>
<td>0.608</td>
<td>0.547</td>
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<td>0</td>
</tr>
<tr>
<td>AFSWA</td>
<td>42.520</td>
<td>0.377</td>
<td>0.595</td>
<td>0.528</td>
<td>1</td>
<td>0</td>
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### Table 2: Objective metrics produced by different filters for Lena corrupted by 50% impulse noise

<table>
<thead>
<tr>
<th>Filters</th>
<th>PSNR</th>
<th>MAE</th>
<th>$\xi_1$</th>
<th>$\xi_2$</th>
<th>MD</th>
<th>FA</th>
</tr>
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<tbody>
<tr>
<td>ROM 7*7</td>
<td>26.934</td>
<td>6.001</td>
<td>4.532</td>
<td>3.614</td>
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<td>118324</td>
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<tr>
<td>Median 7*7</td>
<td>26.973</td>
<td>5.986</td>
<td>4.565</td>
<td>3.566</td>
<td>17</td>
<td>110693</td>
</tr>
<tr>
<td>CWMF 7*7</td>
<td>27.139</td>
<td>5.573</td>
<td>4.305</td>
<td>3.500</td>
<td>81</td>
<td>96079</td>
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<tr>
<td>MMF 5*5</td>
<td>27.545</td>
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<td>4.289</td>
<td>5.099</td>
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<td>124657</td>
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<tr>
<td>PSMF</td>
<td>28.335</td>
<td>3.376</td>
<td>3.369</td>
<td>2.931</td>
<td>29</td>
<td>4061</td>
</tr>
<tr>
<td>LRCF</td>
<td>28.135</td>
<td>3.666</td>
<td>3.011</td>
<td>2.637</td>
<td>105</td>
<td>16</td>
</tr>
<tr>
<td>BDND</td>
<td>29.995</td>
<td>3.001</td>
<td>2.747</td>
<td>2.822</td>
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<td>114</td>
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<tr>
<td>NAFSM</td>
<td>33.01</td>
<td>2.371</td>
<td>2.195</td>
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<tr>
<td>FMLAWK</td>
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<td>AFSWA</td>
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<td>2.065</td>
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### Table 3: Objective metrics produced by different filters for Lena corrupted by 90% impulse noise

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<th>Filters</th>
<th>PSNR</th>
<th>MAE</th>
<th>$\xi_1$</th>
<th>$\xi_2$</th>
<th>MD</th>
<th>FA</th>
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<tbody>
<tr>
<td>ROM 9*9</td>
<td>9.892</td>
<td>54.018</td>
<td>5.992</td>
<td>12.315</td>
<td>44</td>
<td>159</td>
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<tr>
<td>Median 9*9</td>
<td>9.647</td>
<td>53.408</td>
<td>5.965</td>
<td>12.310</td>
<td>50</td>
<td>017</td>
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<tr>
<td>CWMF 9*9</td>
<td>9.410</td>
<td>56.000</td>
<td>6.028</td>
<td>12.640</td>
<td>69</td>
<td>175</td>
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<tr>
<td>PSMF</td>
<td>12.380</td>
<td>31.894</td>
<td>6.379</td>
<td>5.143</td>
<td>4224</td>
<td>12</td>
</tr>
<tr>
<td>LRCF</td>
<td>7.356</td>
<td>85.775</td>
<td>6.203</td>
<td>10.473</td>
<td>538</td>
<td>763</td>
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<tr>
<td>BDND</td>
<td>16.181</td>
<td>13.354</td>
<td>6.182</td>
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<td>539</td>
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<tr>
<td>NAFSM</td>
<td>24.600</td>
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<td>5.944</td>
<td>549</td>
<td>0</td>
</tr>
<tr>
<td>FMLAWK</td>
<td>23.740</td>
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<td>5.503</td>
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<td>0</td>
</tr>
<tr>
<td>AFSWA</td>
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<td>4.956</td>
<td>5.092</td>
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### Table 4: Objective metrics produced by different filters for Lena corrupted by 50% impulse noise

<table>
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<tr>
<th>Filters</th>
<th>PSNR</th>
<th>MAE</th>
<th>$\xi_1$</th>
<th>$\xi_2$</th>
<th>MD</th>
<th>FA</th>
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<tbody>
<tr>
<td>ROM 3*3</td>
<td>29.257</td>
<td>4.989</td>
<td>3.410</td>
<td>2.587</td>
<td>2</td>
<td>217722</td>
</tr>
<tr>
<td>Median 3*3</td>
<td>29.764</td>
<td>4.517</td>
<td>3.385</td>
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<td>0.986</td>
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Fig. 6 shows the edge images of the restored outputs from Lena image corrupted with 10% noise level for NAFSM, FMLAWK and the proposed AFSWA filters.
the pixels will participate in the refinement of corrupted pixels. Majority of cases in which there will not be sufficient uncorrupted pixels in the current window will result in wrongly detecting many impulses as correct pixels.

Case 4: If the noise is high and the threshold, $T_1$ is high: there will not be many uncorrupted pixels in the window; all the pixels will participate in the refinement of corrupted pixels. However, in some rare cases where there will be sufficient uncorrupted pixels in the current window will result in wrongly detecting some correct pixels as impulses. The threshold, $T_2$ used for deciding the participation of a pixel in the uncorrupted set, $\psi$ although does not have much impact on the behaviour of the filtering scheme in the case of high noise impulse levels, provides much deviation in the restored image if its value is very less or very high as can be noted from Table 8. Table 9 shows the PSNR obtained from Lena image for different $T_3$ values against various impulse noise levels. It is to be noted that best PSNR values are obtained for $T_3 = 4$. For experimental purposes, we set the values of thresholds, $T_1$, $T_2$, $T_3$ as 15, 0.5 and 4, respectively. We set $n_1$ and $k$ to 4 and the window size, $W_2$ and $W_3$ to 3.

## 5 Conclusion

The proposed AFSWA filter is designed for the restoration of digital images that are corrupted with salt and pepper impulse noise. The initial part of the impulse detection scheme used min/max check for differentiating non-impulsive pixels from that of impulsive pixels. The detected impulsive pixels are once again refined by checking their edge nature by determining weighted directional distances. The fuzziness in the amount of impulse corruption and similarity among uncorrupted pixels is utilised by, respectively, using the traditional SMALL and modified Gaussian functions for better impulse detection, signal restoration and details-preservation. The experimental analysis favoured the proposed filter at all impulse noise ratios in terms of subjective and objective metrics.
The proposed filter is designed for the restoration of only salt and pepper impulse corrupted digital images. As a future work the proposed filter can be extended to restore the digital images corrupted by other impulse noise models that include the random valued impulses and the impulses following Cauchy or Gaussian distribution. This can be attempted by accommodating more intelligent hybrid soft-computing techniques into the domain of impulse restoration and by the homogeneity analysis of the corrupted image using the multi-resolution theory. Moreover, the optimisation of the parameters used in the proposed algorithm can be extended in the future.

7 References