Impulse Noise Reduction Using Combined Fuzzy and Non Local Means Approach

B.L.Benisha Bennet¹, P.Karthikeyan², Dr.S.Vasuki³

¹, ², ³Department of ECE, Velammal College of Engineering and Technology, Madurai, India

¹bl.benisha@gmail.com, ²kp.karth@gmail.com

Abstract—Impulse noise reduction is an active area of research in image processing. In this paper we propose a two phase scheme to detect and correct the impulse noise. In the first phase a fuzzy detection is being used, to identify pixels that are likely to be contaminated by impulse noise. In the second phase the noisy corrupted image is being subjected to a non local means filter which efficiently filter out the noisy pixels. Extensive experiments are performed to show that the proposed technique gives high performance compared to other models particularly with high noise densities. The experimental result is based on well known global as well as local quantitative measure like peak-signal-to-noise-ratio (PSNR).

Key words—fuzzy detection, impulse noise, non local means filter.

I. INTRODUCTION

Most of the digital images could be corrupted by noise during image acquisition and transmission due to malfunctioning of pixels. Impulse noise is more common among them, which is caused by some pixel errors in camera sensors, defective memory locations in hardware, or broadcast in a noisy channel [1]. Two common types of impulse noise are salt-and-pepper noise and random valued noise. For salt-and-pepper noise corrupted images, the noisy pixels take only the maximum and minimum values and for images that are corrupted by random valued noise, the noisy pixels takes the random values. It is therefore necessary to remove the impulse noise in images before using them for other image processing techniques like detection of edges, segmentation, restoration etc. Several filtering techniques have been proposed to address the removal of impulse noise. The median filter was once the most admired nonlinear filter for removing impulse noise because of its good denoising power and computational efficiency [2]. However when the noise level is greater than 50%, some details and edges of the original image is smeared by the filter. To obtain enhanced performance several modified median filters are proposed, such as Weighted Median Filter (WMF) [3]. Recursive Weighted Median Filter (RWMF) [4], adaptive median filter [5], Center Weighted median filter [6]. All these filters are implemented uniformly over the image without considering whether the centre pixel is corrupted or not. To overcome this problem a two stage technique is being followed whereby in stage one, the noisy pixel is detected and in second stage the noisy detected pixel is filtered out. A two stage filter called as switched median filter [7] is introduced which has improved denoising capability and efficiency compared to uniformly distributed median filter technique. Later on various improvements are being done to further improve the denoising capability.

In this paper we propose a Fuzzy Rank Ordered Difference (FROD) technique to detect the presence of impulse noise which is a twostep procedure. In the first step we identify the pixels that are clearly noisy or clearly noise free. The second step is used to detect the noisy pixels that are difficult to classify. After detecting the corrupted pixels a non local means filter is used which efficiently filter out the noisy pixels and finally we obtain the output image which has a high PSNR compared to other techniques.

The rest of the paper is organized as follows. The part II deals with the effective noise detection technique using fuzzy Rank Ordered Detection technique. The filtering procedure using non local means filter is discussed in part III. Experimental results are shown in part IV and the conclusion is given in part V.

II. FUZZY RANK ORDERED DEFEERENCE IMPULSE NOISE DETECTION

A. Impulse noise model
Impulse noise mainly occurs in a digital image due to pixel errors in camera sensors, defective memory locations in hardware, or broadcast in a noisy channel. When an image is affected by impulse noise only a particular portion of the image gets corrupted. The impulse noise may be of two types fixed (salt and pepper) and random valued noise. The salt and pepper noise could take either the maximum or minimum value and the random valued noise takes any of the values in the dynamic range. Random valued noise is more difficult to be removed than salt and pepper. So it is very necessary to remove the random valued noise. The proposed technique deals with the removal of the random valued noise.

B. Fuzzy rank ordered difference

Consider an image which is centered at a pixel \( x_i \) with a window \( w_x \) where each pixel \( x_j \in w_x \) and \( w_x^c \) is the set of neighbours of \( x \) in \( w_x \) ie, \( w_x^c = w_x - \{x\} \). In this technique we use the fuzzy metric to obtain the fuzzy distances \( d_{x,j} = M(x, x_j), x_j \in w_x^c \). The fuzzy metric is sensitive to impulse noise. If impulse noise affects either one of \( x \) or \( x_j \) it deals with the lowest nearness value among its components. If the difference values becomes larger fuzzy metric drops rapidly. Now the fuzzy distances are arranged in a descending order \( s_1(x) \geq s_2(x) \ldots \ldots s_{n^2-1}(x) \) and hence \( s_j(x) \) is the \( j \)th largest value of \( d_{x,j} \). Hence fuzzy rank ordered difference is given as

\[
\text{FROD}_m(x) = \prod_{j=1}^{m} s_j(x) \tag{1}
\]

Where \( m < n^2 - 1 \) is the filter parameter. The noise detection scheme is divided in to two stages. In the first stage an image is clearly classified as noisy or noise free and in the second stage the pixels that are difficult to classify are detected. If \( \text{FROD}_m(x) \) is greater than a high threshold value \( t_{h1} \), then the pixels are classified as clearly noisy free. Otherwise if \( \text{FROD}_m(x) \) is lower than a low threshold value \( t_{h2} \) then the pixels are classified as noisy. If \( t_{h1} \leq \text{FROD}_m(x) \leq t_{h2} \) then it is difficult to classify for this we use a third threshold value \( t_{h3} \), for \( \text{FROD}_m(x) \) which is calculated from the pixel values excluding the classified pixels where \( m^<m \) is another filter parameter. If \( \text{FROD}_m(x) > t_{h3} \) then \( x \) is classified as noise free else \( x \) is classified as noisy.

C. Algorithm for fuzzy rank ordered difference

1. For every pixel in the image compute \( d = \text{FROD}_m(x) \).
2. If \( d > t_{h1} \) then the pixels used in \( \text{FROD}_m(x) \) are classified as noise free.
3. Else if \( d > t_{h2} \) then the pixels are classified as noisy.
4. If \( t_{h1} < d < t_{h2} \) then the pixels are classified as non-diagnosed.
5. For each non-diagnosed pixels compute \( d = \text{FROD}_m(x) \), not taking in to account that are classified already.
6. If \( d > t_{h3} \) then the pixels used in \( \text{FROD}_m(x) \) are classified as noise free.
7. Else the pixels in \( \text{FROD}_m(x) \) are classified as noisy.

III. NON LOCAL MEANS FILTERING

A. Previous Methods, Motivation and Problem Statement

Most denoising algorithms make two assumptions about the noisy image. These assumptions lead to blurring and loss of detail in the resulting denoised images. The white noise affect the image is the first assumption. This means that the noise contains all frequencies namely, low and high. Due to the higher frequencies namely, the noise is oscillatory or non-smooth. The true image is smooth or piecewise smooth is the second assumption. This means the true image or patches of the true image only contain low frequencies. Previous methods attempt to separate the image into the smooth part (true image) and the oscillatory part (noise) by removing the higher frequencies from the lower frequencies. Nevertheless, not all images are smooth. Images can have well defined details and structures which have high frequencies. When the high frequencies are detached, the high frequency content of the true image will be removed along with the high frequency noise because the methods cannot tell the difference between the noise and true image. This will result in a loss of fine detail in the denoised image. Also, nothing is done to reduce the low frequency noise from the image. Low frequency noise will be there in the image even after denoising. Due to this loss of fine detail Buades developed the non-local means algorithm.

B. Non-local Means Theory

The non-local means algorithm does not make any such assumptions about the image as other methods. Instead it assumes the image contains widespread self-similarity. Efros and Leung initially developed the concept of self-similarity for texture synthesis. An example of self-similarity is displayed in Figure 1 below. The figure pictures three pixels \( p \), \( q_1 \), and \( q_2 \) and their respective neighbourhoods. The neighbourhoods of pixels \( p \) and \( q_1 \) are similar, but the neighbourhoods of pixels \( p \) and \( q_2 \) are not similar. Adjacent pixels tend to have similar neighbourhoods, but non-adjacent pixels will also have similar neighbourhoods when there is structure in the image. For example, in Figure 1 most of the pixels in the same column as \( p \) will have similar neighbourhoods to \( p \)'s neighbourhood. The self-similarity assumption can be exploited to denoise an image. Pixels with similar neighbourhoods can be used to determine the denoised value of a pixel. Pixels \( p \) and \( q_1 \) have similar
neighbourhoods, but pixels p and q2 do not have similar
neighbourhoods. Because of this, pixel q1 will have a
stronger influence on the denoised value of p than q2.

![Image](image.png)

Fig. 1. Example showing self-similarity in an image

C. Non-local Means Method

Pixels p of the non-local means denoised image is
computed with the following formula:

\[ NL(V)(P) = \sum_{q \in \Omega} w(p, q)V(q) \tag{2} \]

Where V is the noisy image, and weights w (p, q) meet
the following conditions \(0 \leq w(p, q) \leq 1\) and \(\sum_q w(p, q) = 1\).
Each pixel is a weighted average of all the pixels in the
image. The weight depends on the similarity between
the neighbourhoods of pixels p and q \([1, 2]\). For example, in
Figure 1 above the weight w (p, q1) is much greater than w
(p, q2) because pixels p and q1 have similar
neighbourhoods and pixels p and q2 do not have similar
neighbourhoods. In order to compute the similarity, a
neighbourhood must be defined. Let \(N_i\) be the square
of the centred neighbourhood about pixel i with a user-
defined radius \(R_{sim}\). The weights can then be computed
using the following formula

\[ w(i, j) = e^{-\frac{||N(x_i) - N(x_j)||^2}{h^2}} \tag{3} \]

Where \(N(x_i)\) is the vector of location \(x_i\), h is the smoothing
parameter and \(a\) is the variance of normal distribution.
Equation (2) from above does have a special case when
\(q = p\). This is because the weight \(w(p, p)\) can be much
larger than the weights from every other pixel in the image.
By definition this makes intellect because every
neighborhood is comparable to itself. To avert pixel p
from over-weighing itself let \(w(p, p)\) be equivalent to the
maximum weight of the other pixels.

D. Non-local Means Parameters

The non-local means algorithm has three parameters. The
foremost parameter, \(h\), is the weight-decay control
parameter which controls the weights which lay on the
decaying exponential curve. If \(h\) is too little, not enough
noise will be removed. If \(h\) is too high, the image will
become blurry. While an image has white noise with a
standard deviation of \(h\) should be set between 10 and 15.
The second parameter, \(R_{sim}\), is the radius of the
neighborhoods that is used to determine the similarity
between two pixels. If \(R_{sim}\) is too large, no comparable
neighborhoods will be found, but if it is too small, too
many comparable neighborhoods will be found. Common
values of \(R_{sim}\) are 3 and 4 to give neighborhoods of size
7x7 and 9x9, respectively. \(R_{win}\) is the third parameter
which gives the radius of a search window. Due to the
inadequacy of taking the weighted average of every pixel
for every pixel, it will be condensed to a weighted average
of all pixels in a window. The window is centered at the
existing pixel being computed. Frequent values for \(R_{win}\)
are 7 and 9 to give windows of size 15x15 and 19x19,
respectively. With this alter the algorithm will take a weighted
average of \(15^2\) pixels rather than a weighted average of \(N^2\) pixels
for an NxN image.

![Image](image.png)

Fig. 2. Profile of filter F when \(R_{sim} = 4\).

IV. COMBINED FROD-NLM

The combined FROD-NLM technique provides a high
value of PSNR of different noise densities. The fuzzy rank
ordered difference provides good noise detection even
when the noise density is more. The properly detected
noise is then given as input to the non local means filter
which filter out the noise in a definite manner using the
concept of redundancy. The overall technique is shown in
Fig. 3
V. RESULTS

The output is being simulated using MATLAB and the proposed method is tested with pepper image with a noise level of 40%. Fig.4(a,b,c,d,e,f,g) are the original image, noisy image, traditional median image, weighted median image, vector median image, recursive weighted median image, FROD-NLM image. Table 1 shows the PSNR value obtained for noise level of 40% and 50%. It is found that our proposed technique have the high PSNR value. Also visually it is seen that FROD-NLM has the well filtered image. As we obtain from the result that the FROD-NLM technique produces output with high PSNR value also visually it is seen that our technique yields the best result.

Fig. 4(a) denotes the original Pepper image. 4(b) denotes the salt and pepper noise added with variance of 0.4. 4(c) denotes the output of traditional median filter. 4(d) denotes weighted median filter output. 4(e) denotes the vectored median filter. 4(f) denotes the recursive weighted median filter. 4(g) denotes the FROD-NLM filter.
TABLE 1
PSNR VALUE OF PEPPER IMAGE WITH NOISE LEVEL OF 40% AND 50%

<table>
<thead>
<tr>
<th>Method</th>
<th>Pepper</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>40%</td>
</tr>
<tr>
<td>Traditional Median</td>
<td>23.1</td>
</tr>
<tr>
<td>Weighted Median</td>
<td>21.4</td>
</tr>
<tr>
<td>Vectored Median</td>
<td>24.7</td>
</tr>
<tr>
<td>Recursive Weighted</td>
<td>26.5</td>
</tr>
<tr>
<td>FROD-NLM</td>
<td>33.5</td>
</tr>
</tbody>
</table>

VI. CONCLUSION

In this we proposed a fuzzy rank ordered detection which efficiently detected the presence of impulse noise. The noise detected image is then given as input to the non local means filter. The proposed filter filtered the noise detected image efficiently, it has high the PSNR value and also visually our technique is found good.

REFERENCES


