Mean – Median Filtering For Impulsive Noise Removal

N.Sakthivel¹, L.Prabhu²

¹,²Assistant professor,
Department of Electronics and communication engineering,
Excel college of Engineering and technology,
Komarapalayam – 03

¹mask.kns@sify.com
²prabhuinigo36@gmail

Abstrak – The objective of this paper is a new Mean-Median filtering for denoising extremely corrupted images by impulsive noise. Whenever an image is converted from one form to another, some of degradation occurs at the output. Improvement in the quality of these degraded images can be achieved by the application of Restoration and/or Enhancement techniques. Noise removing is one of the categories of Enhancement. Removing noise from the original signal is still a challenging problem. Mean filtering fails to effectively remove heavy tailed noise & performance poorly in the presence of signal dependent noise. The successes of median filters are edge preservation and efficient attenuation of impulsive noise. An important shortcoming of the median filter is that the output is one of the samples in the input window. Based on this mixture distributions are proposed to effectively remove impulsive noise characteristics. Finally, the results of comparative analysis of mean-median algorithm with mean, median filters for impulsive noise removal show a high efficiency of this approach relatively to other ones.

Key Words – Image Enhancement; Impulse noise; linear filters; Non Linear filters; Mean filter; Median filter.

1 Introduction

Digital images play an important role both in daily life applications such as satellite television, magnetic resonance imaging, computer tomography as well as in areas of research and technology such as geographical information systems and anatomy. Image restoration is an important area of digital image processing which involves the objective improvement of the degraded digital image based on the prior knowledge of the mathematical or probabilistic model of image degradation. During image acquisition through sensors or communication channels, image may be contaminated by noise. The interference of noise in images might affect the results for some processing, such as edge detection, image segmentation, data compression and object recognition. Therefore, the process of image restoration or noise filtering should be taken on the image before other image processing takes place. Attenuate noise is an essential task in digital image processing. The challenge of this task is how to reduce noise while keeping the image details. There are many works on the restoration of images
corrupted by impulse noise. There are two basic approaches to image denoising, spatial filtering and Transform domain filtering methods. A traditional way to remove noise from image data is to employ spatial filters. Spatial filters can be further classified into non-linear and linear filters. Linear filters have been the dominating filter class through the history of signal processing, due mainly to the sound theoretical basis provided by the theory of linear systems and the computational efficiency of linear filtering algorithms. Despite the elegant linear system theory, not all signal processing problems can be satisfactorily addressed through the use of linear filters. Linear filters tend to blur sharp edges, fail to remove heavy tailed distribution noise effectively, and perform poorly in the presence of signal dependent noise. With non-linear filters, the noise is removed without any attempts to explicitly identify it. A non-linear filter has been proven very useful is the class of median based filters. The success of median filters is based on two intrinsic properties: (i) Edge Preservation and (ii) Efficient noise attenuation with robustness against impulsive type noise. An important shortcoming of the median that has hampered its use in many other fields is that the filter output is always constrained, by definition, to be one of the samples in the input window. For example, that the median loses as much as 40% efficiency over the sample mean when used as a location estimator in Gaussian environments. Accordingly mixture distributions are proposed to model the underlying Gaussian and impulsive noise characteristics encountered in many applications.

2 Image Enhancement Overview

Whenever an image is converted from one form to another, such as digitizing, transmitting, scanning, etc., some of degradation occurs at the output. Secondly, no imaging system, however accurate it be can produce an exact replica of the scene (or ideal image). Improvement in the quality of these degraded images can be achieved by the application of enhancement technique. The principle objective of enhancement is to process an image so that the result is more suitable than the original image for a specific application. The word specific is important, because the enhancement technique which is suitable for biomedical images can be total catastrophe for remotely sensed images. Secondly, the quality of an image depends on the purpose for which the image is acquired or displayed. Image Enhancement approaches fall into two broad categories. There is spatial domain, Frequency domain. The term spatial domain refers to the image plane itself, and approaches in this category are based on direct manipulation of pixels in an image.

\[ g(r, c) = T(g(r, c), Q(r, c)) \]  \[ \text{... (1)} \]

For all \( r \) and \( c \) where \( Q(r, c) \) is the set of gray levels of neighboring pixels. \( T \) is the operator, in general, defined over some neighborhood of \( (r, c) \), and the operation is the convolution. Some of these operators are also called filters. The term frequency domain processing techniques are based on modifying the Fourier transform of an image.

\[ G(u, v) = J(u, v) G(u, v) \text{ for all } u \text{ and } v \]  \[ \text{... (2)} \]

Image noise is the random variation of brightness or color information in images produced by the sensor and circuitry of a scanner or digital camera. Image noise can also originate in film grain and in the unavoidable shot noise of an ideal photon detector. Image noise is generally regarded as an undesirable by-product of image capture. Although these unwanted fluctuations became known as "noise" by analogy with unwanted sound, they are inaudible and actually beneficial in some applications, such as dithering. A particular type of interference is Impulse Noise. This is typically caused by sources such as electrical machinery and switchgear, and consists of short high energy bursts of wideband noise. This is a standard noise impulse defined by ANSI for test purposes called
ANSI T1.413-1988 Test Impulse 1. The first thing to note is that the x-axis of the plot is time, not frequency as it would be on a spectrum analyzer. The duration of the impulse is quite short, although its amplitude is quite high. Secondly, the vertical scale is in dB (not dBm) which means that the level of the impulse at any point is measured relative to the signal on the line, rather than being an absolute power measurement. Impulse noise does not affect xDSL services as much as baseband services, because of error correction, but it nevertheless an important influence on lines and should be measured as part of an overall noise audit. The line is connected to the instrument through a band pass filter, which passes the band of frequencies of interest which could affect the service. For baseband services this bandwidth is defined by ITU O.71. Only impulses over a certain level would affect the service, so a threshold detector is used to discriminate these from any lower level transients. There is also a minimum time period during which transients are counted as impulses, so that the events counter only increments for each new impulse and not multiple times within an impulse. In a simple system only the number of impulses is counted. In more advanced instruments a record is also made of the time during which the noise level exceeds the threshold, and the number of seconds containing one or more impulse.

3 Impulse Filters – an Overview

Filters are broadly classified into two types. There are linear filters & Non Linear filters

3.1 Linear filters

A linear filter applies a linear operator to a time-varying input signal. Linear filters are very common in electronics and digital signal processing. But they can also be found in mechanical engineering and other technologies. They are often used to eliminate unwanted frequency from an input signal or to select a desired frequency among many others. There are a wide range of types of filters and filter technologies, of which this article will present an overview. Linear filters can be divided into two classes. There are Infinite impulse responses (IIR) and Finite impulse response (FIR) filters.

3.2 Non Linear filters

A nonlinear filter is a signal-processing device whose output is not a linear function of its input. Terminology concerning the filtering problem may refer to the time domain (state space) representation of the signal or to the frequency domain representation of the signal. When referring to filters with adjectives such as "band pass, high pass, and low pass" one has in mind the frequency domain. When resorting to terms like "additive noise", one has in mind the time domain, since the noise that is to be added to the signal is added in the state space representation of the signal. The state space representation is more general and is used for the advanced formulation of the filtering problem as a mathematical problem in probability and statistics of stochastic processes.

3.3 Mean filters

The Average (mean) filter smoothes image data, thus eliminating noise. This filter performs spatial filtering on each individual pixel in an image using the grey level values in a square or rectangular window surrounding each pixel. The average filter computes the sum of all pixels in the filter window and then divides the sum by the number of pixels in the filter window: Filtered pixel = (a1 + a2 + a3 + a4 ... + a9) / 9. The mean filter is a simple sliding-window spatial filter that replaces the center value in the window with the average (mean) of all the pixel values in the window. The window, or kernel, is usually square but can be any shape. An example of mean filtering of a single 3x3 window of values is
shown below. Common names of mean filter is Mean filtering, Smoothing, Averaging, Box filtering.

### 3.4 Median filters

The median filter is also a sliding-window spatial filter, but it replaces the center value in the window with the median of all the pixel values in the window. As for the mean filter, the kernel is usually square but can be any shape. In order: 0, 2, 3, 3, 4, 6, 10, 19, 97. Center value (previously 97) is replaced by the median of all nine values (4). The median filter would also return a value of 5, since the ordered values are 1, 2, 3, 4, 5, 6, 7, 8, 9. For the second (bottom) example, though, the mean filter returns the value 16 since the sum of the nine values in the window is 144 and 144 / 9 = 16. This illustrates one of the celebrated features of the median filter: its ability to remove ‘impulse’ noise (outlying values, either high or low). The median filter is also widely claimed to be ‘edge-preserving’ since it theoretically preserves step edges without blurring. However, in the presence of noise it does blur edges in images slightly.

### 3.5 Mean Median filters

Linear filters too tend to blur sharp edges, destroy lines and other fine image details, and perform poorly in the presence of signal dependent noise. The wiener filtering method requires the information about the spectra of the noise and the original signal and it works well only if the underlying signal is smooth. Wiener method implements spatial smoothing and its model complexity control correspond to choosing the window size. Mean filter is the optimal linear filter for Gaussian noise in the sense of mean square error. However, mean filtering fails to effectively remove heavy tailed noise and performs poorly in the presence of signal dependent noise. An important shortcoming of the median that has hampered its use in many other fields is that the filter output is always constrained, by definition, to be one of the samples in the input window. For example, that the median loses as much as 40% efficiency over the sample mean when used as a location estimator in Gaussian environments. Overcome of the mean and median filtering, proposed the new method of impulse noise removal, entitled “Mean – Median filtering for impulsive noise removal”. Mean - Median FILTER: Mean Filter+ Median Filter. The Mean - Median Filter output is a combination of the sample mean and sample median. Where observation samples are weighted uniformly. This property of Mean - Median filters constrains them to the class of smoothers taking frequency selective filtering capabilities.

### 4 Experimental Results

The proposed filter is analyzed through the determination of following. Peak signal to noise ratio, Mean square error. The phrase peak signal-to-noise ratio, often abbreviated PSNR, is an engineering term for the ratio between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation. Because many signals have a very wide dynamic range, PSNR is usually expressed in terms of the logarithmic decibel scale. The PSNR is most commonly used as a measure of quality of reconstruction of loss compression codes (e.g., for image compression). The signal in this case is the original data, and the noise is the error introduced by compression. When comparing compression codes it is used as an approximation to human perception of reconstruction quality, therefore in some cases one reconstruction may appear to be closer to the original than another, even though it has a lower PSNR (a higher PSNR would normally indicate that the reconstruction is of higher quality). One has to be extremely careful with the range of validity of this metric; it is only conclusively valid when it is used to compare results from the same codec (or codec type) and same content.

The Mean Square Error (MSE) and the Peak Signal to Noise Ratio (PSNR) are the two error metrics
used to compare image compression quality. The MSE represents the cumulative squared error between the compressed and the original image, whereas PSNR represents a measure of the peak error. The lower the value of MSE, the lower the error.

To compute the PSNR, the block first calculates the mean-squared error using the following equation:

$$\text{MSE} = \frac{\sum_{m,n} [I_1(m,n) - I_2(m,n)]^2}{M \times N}$$  \hspace{1cm} \text{... (3)}

In the previous equation, M and N are the number of rows and columns in the input images, respectively. Then the block computes the PSNR using the following equation:

$$\text{PSNR} = 10 \log_{10} \left( \frac{R^2}{\text{MSE}} \right)$$  \hspace{1cm} \text{... (4)}

In the previous equation, R is the maximum fluctuation in the input image data type. For example, if the input image has a double-precision floating-point data type, then R is 1. If it has an 8-bit unsigned integer data type, R is 255, etc.

Mean filtering is most commonly used as a simple method for reducing noise in an image. Shows the original corrupted by Salt & pepper noise with a mean of zero. Shows the effects of applying 3×3 mean filter. Note that the noise is less apparent, but the image has been `softened'.

The median filter is much better at preserving sharp edges than the mean filter. Shows the original corrupted by Salt & pepper noise with a mean of zero. It is the result of 3×3 median filtering. The median filter is sometimes not as subjectively good at dealing with large amounts of noise as the mean filter. Where median filtering really comes into its own is when the noise produces extreme `outlier' pixel values, as for instance in which has been corrupted with `salt and pepper' noise, i.e. bits have been flipped with probability 1%. Median filtering this with a 3×3 neighborhood produces in which the noise has been almost eliminated with to the underlying image.
The Mean – Median filter is much better at remove the salt and pepper noise. Shows the original corrupted by Salt & pepper noise with a mean of zero. Applying a 3×3 Mean - Median filter produces which has been corrupted with `salt and pepper’ noise. Mean - Median filtering this with a 3×3 neighborhood produces in which the noise has been entirely eliminated with no degradation to the underlying image. Finally the comparative statement is the Mean – Median filter is effectively removing the impulse noise for salt and pepper noise.

4.1 Experimental Results

The performance of the proposed algorithm (Mean – Median) was tested against Mean Filter and the Median filters on a standard onion.png shown fig are used here for analysis. Objective comparisons of the performances of these filters (Mean, Median, and Mean - Median) on images corrupted by various levels of impulsive noise ratios are made with the Mean Square Error (MSE) values and the Peak Signal to Noise ratios (PSNR) of the images restored by them.

For the final restored image of size M*N, the PSNR is

\[ PSNR = 10 \log_{10} \left( \frac{R^2}{MSE} \right) \]  \hspace{1cm} \ldots (5)

Where Mean Square Error, MSE is

\[ MSE = \frac{\sum_{M,N} [I_1(m,n) - I_2(m,n)]^2}{M \times N} \] \hspace{1cm} \ldots (6)

With respect to the noise free original image

Tables 2, 3, 4 tabulate the objective metrics, PSNR, MSE and variance of the Mean, Median, Mean – Median filters. Though the median is less complex at smaller noise ratios, an appreciable improvement in computational efficiency is felt at higher noise ratios by the Mean – Median filter. The PSNR and MSE and variance values add to the objective eminence of the Mean – Median filter over the mean and median filters.

Tabulation for PSNR

TABEL 2: PSNR of Mean, Median, and Mean – Median filters at different noise levels

<table>
<thead>
<tr>
<th>Noise Ratio</th>
<th>Mean Filter</th>
<th>Median Filter</th>
<th>Mean – Median Filter</th>
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<tbody>
<tr>
<td>1</td>
<td>0.00</td>
<td>36.4164</td>
<td>40.8506</td>
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<tr>
<td>2</td>
<td>0.02</td>
<td>34.4200</td>
<td>40.5229</td>
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<tr>
<td>3</td>
<td>0.04</td>
<td>32.9426</td>
<td>40.3665</td>
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<tr>
<td>4</td>
<td>0.06</td>
<td>32.5447</td>
<td>39.9015</td>
</tr>
<tr>
<td>5</td>
<td>0.08</td>
<td>31.8153</td>
<td>39.5712</td>
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<td>6</td>
<td>0.10</td>
<td>31.4166</td>
<td>39.3215</td>
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<td>7</td>
<td>0.12</td>
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<td>0.14</td>
<td>30.8909</td>
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<td>9</td>
<td>0.16</td>
<td>30.4316</td>
<td>38.4993</td>
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<td>0.18</td>
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<td>0.20</td>
<td>30.3220</td>
<td>38.0680</td>
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</table>

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Tabulation for MSE

TABEL 3: MSE of Mean, Median, and Mean – Median filters at different noise levels

<table>
<thead>
<tr>
<th>Noise Ratio</th>
<th>Mean Filter</th>
<th>Median Filter</th>
<th>Mean – Median Filter</th>
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<tr>
<td>1</td>
<td>14.8401</td>
<td>5.3459</td>
<td>5.3459</td>
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<td>2</td>
<td>23.5005</td>
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<td>5.9445</td>
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<td>3</td>
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<td>36.1921</td>
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Tabulation for Variance

TABEL 4: Variance of Mean, Median, and Mean – Median filters at different noise levels

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<tr>
<th>Noise Ratio</th>
<th>Mean Filter</th>
<th>Median Filter</th>
<th>Mean – Median Filter</th>
</tr>
</thead>
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<tr>
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<td>87.2850</td>
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<td>86.7564</td>
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<td>2</td>
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<td>88.4172</td>
<td>86.7575</td>
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<td>3</td>
<td>88.2858</td>
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<td>4</td>
<td>88.3893</td>
<td>88.3238</td>
<td>86.6062</td>
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<td>5</td>
<td>89.4839</td>
<td>88.3005</td>
<td>86.6352</td>
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<td>6</td>
<td>88.5868</td>
<td>88.5103</td>
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<td>8</td>
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</table>

The improved visual subjectiveness can be felt by the restoration of the proposed Mean – Median as against the Mean and Median filters. The output of Mean – Median from a highly corrupted image is devoid of impulse patches that are vivid in the output of Mean and Median adding to the visual clarity of Mean – Median’s restoration. It is worth noting that at uneven noise levels, Mean – median filter performs very well in comparison with other methods in terms of computational efficiency as demonstrated in the tables 2, 3, 4.

4 Conclusion

A new Mean – Median filter is proposed to remove impulse noises that can much acceptable, recognizable image restoration. An ideal denosing practical procedure requires a priori knowledge of the noise, whereas a procedure may not have the required information about the variance of the noise or the noise model. Thus, most of the algorithms assume known variance of the noise and the noise model to compare the performance with different algorithms. The proposed filter is analyzed through
the determination of filter output variance. Performance of denoising algorithms is measured using quantitative performances such as PSNR and MSE as well as in terms of visual quality of the images. The significant difference in mean square error (MSE) and Peak signal to noise ratio (PSNR) with other mean and median filters quantifies the superiority of the Mean – Median filter. From the Graphical representation and visual output, it is very clear that from low level impulse noise levels to very high level impulse noise levels Mean – Median Filter superbly outperforms the next best Median as well as the Mean filters algorithms. The simulation results provided proposed filter gives the fine detail preservation and impulse noise removal characteristics, may use too many signal and image processing applications.

The restoration of Mean – Median filter is more identifiable than the Mean and Median filters which is more degradation.

5 Simulation Results

PSNR Graph for various Noise Level

![PSNR Graph](image1.png)

Fig. 2: PSNR outputs of Mean, Median, and Mean – Median Filters

MSE Graph for various Noise Level

![MSE Graph](image2.png)

Fig.3: MSE outputs of Mean, Median, and Mean – Median Filters
Variance Graph for various Noise Level

Fig. 5: Variance outputs of Mean, Median, and Mean – Median Filters

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