DYNAMIC INTELLIGENT MEAN FILTER FOR IMPULSE NOISE SUPPRESSION IN 2D IMAGES

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Abstract

Noise, as random, unwanted data, appears in images from various sources. So its reduction or removal is an important task in image processing. This study employed an intelligent mean filter, which is an extension of the median filter, adaptive median filter, and the mean filter, to achieve the purpose of noise reduction. The proposed mean filter belongs to the broad class of nonlinear filters. The method is more effective in image processing because it utilizes an intelligent technique to find the mean of a set of pixels in the active window, which is used to perform the filtering process. Impulsive noise is a form of image corruption where each pixel value is replaced with an extremely large or small value that is not related to the surrounding pixel values by a significant probability.

Any pixel that is noisy is replaced with the computed mean. The adaptiveness of the method lies in the size of the filtering window, which is determined by the amount of noise in the window. The filtering process starts with a 3x3 window and extends it to a 5x5 window until it gets to the maximum window size chosen by this technique, which is 9x9. The window size extends from the initial size to the subsequent sizes if the amount of noise pollution in each chosen size is greater than 40% using some approximation schemes. The moving-window architecture is employed to the movement of the window through the entire image in order to aid the filtering process. The performance of the proposed intelligent Mean filter has been evaluated in MATLAB simulations on an image that was subjected to various degrees of corruption with impulse noise. The results demonstrated the effectiveness of the algorithm.

Introduction

The transfer medium, the working conditions and the recording devices of an imaging system are subjected to noise corruption during transmission. Thus, the image quality is reduced and the effectiveness and accuracy of the subsequent processing course, such as edge detection, image segmentation, and pattern segmentation, can be negatively affected. Therefore, it is helpful to remove the noise from the image using an image filter. But the effective removal of the noise is often accomplished at the expense of blurred or even lost features [1].

Noise filtering is an important component in signal processing systems, which is comprised of estimating the amount of the signal that has been degraded by noise. The percentage of noise corruption is calculated by taking the percentage of the degraded pixels in the entire image. Intuitively, when the percentage of the polluted pixel is greater than the percentage of the clean uncorrupted pixel, most of the proposed filtering techniques generate a fairly poor result. The design of a filter will depend on the detection of the type of noise, estimation of the intensity of the noise corruption and the distribution of the noise [2], [3]. Digital image filtering techniques can be categorized into two broad areas: spatial domain filtering and frequency domain filtering. The spatial domain filtering technique is based on the direct manipulation of the image pixels, while the frequency domain filtering technique has to do with modifying the Fourier transform of the image [3].

Various spatial filtering techniques have been proposed for removing impulse noise in the past, and it is well known that linear filters can produce serious image blurring. As a result, nonlinear filters have been widely exploited due to their much improved filtering performance, particularly in relation to impulse noise attenuation and detail preservation. One of the most popular and robust nonlinear filters is the standard median (SM) filter [4], which exploits the rank-order information of pixel intensities within a filtering window and replaces the center pixel with the median value. The SM filter's effectiveness in noise suppression and simplicity of implementation has led to various modifications, such as the weighted median (WM) filter [5] and the center weighted median (CWM) filter [6].

The median filter is implemented by replacing all of the pixels in the activate window with the selected center pixel known as the median. The process replaces the corrupted and also the uncorrupted pixels in the image; the replaced uncorrupted pixels cause a lot of defeat in the image quality. Hence, a tentative solution for circumventing this problem is to implement a noise (impulse noise) detection technique to aid in the filtering process; this identifies only the corrupted pixels that will be replaced, while the uncorrupted pixels remain intact. The switching median filter [1], [7-9] has achieved a lot of significant performance due to the noise detection mechanism that solves the problem of identifying the corrupted pixels in a filtering process.

The most popular approaches for dealing with such impulse noise have centered on median filtering and the rich class of order statistic filters that have emerged from the study of median filters [10], [11]. Recently, variations on the median filtering scheme have been shown, under specific signal/noise models, to deliver improved performance relative to the corresponding traditional methods. To solve the problem of filtering out edge details and image details causing blurring of the image, an intelligent mean filtering scheme is presented in this paper. It exhibits improved performance in removing impulse noise, while preserving the fine details of the 2D image structure.

Impulse (salt-and-pepper) Noise

Impulse noise is a sort of unidirectional impulse-like noise. This category of noise is usually occurs as a result of electromagnetic interference, analog-to-digital converter error, bit error in transmission, malfunctioning pixels in camera sensors or faulty memory locations [8], [11], [12]. Intuitively, when an image is polluted with this kind of noise, it sets some of the pixel values of the region with lower values to the maximum value and also converts some of the pixel values to the minimum value or zero.

Hence, an image that has been corrupted with impulse noise (salt and pepper) appears as bright spots in the dark region and dark spots in the bright region of the image. The uncorrupted pixels remain intact in the image. The percentage of the noise present in the image is calculated by the difference of the total percentage and the percentage of uncorrupted pixels. This can be quantified by finding the percentage of the corrupted pixels. The probability density function of impulse noise is given by:

$$p(z) = \begin{cases} P_a & for \quad z = a \\ P_b & for \quad z = b \\ 0 & otherwise \end{cases} \qquad (1)$$

The probability density function describes the distribution of the impulse noise particles in the image, where a and b are the pixel values in the image. When a happens to be far less than b and most of the image pixels lie in the range around the value of a, then b becomes a distortion with a high intensity appearing as a bright dot or bright spot in that region. Otherwise, when the pixel values lie in the range of b, then a instead becomes the distortion with a lower intensity and appears as a dark dot or dark spot.

If P_a or P_b is zero, then only one kind of situation can occur; that is, whether the spots that appear are either bright or dark in the entire image, which is termed unipolar noise. If neither of the probabilities are zero and both of the dark spots and the white spots are randomly distributed in the entire image, and if the frequency of appearance is approximately equal, then the noise is described as salt-and-pepper impulse noise.

Bipolar impulse noise occurs when an image contains extremely low values in a region where the pixel values are of high intensity and extremely high values in the region where the values are of low intensity. The salt-and-pepper impulse noise and the spots and spikes impulse noise belong to this category of noise, where the values of a and b are referred to as saturated values in the sense that they produce extremely pure white or extremely pure black, corresponding to the minimum and maximum values allowed. Positive (high pixel values) impulses appear white (salt) noise, while the zero impulses appear as black (pepper). For an 8-bit image this means that a = 0 (black) and b = 255 (white) [2], [3].

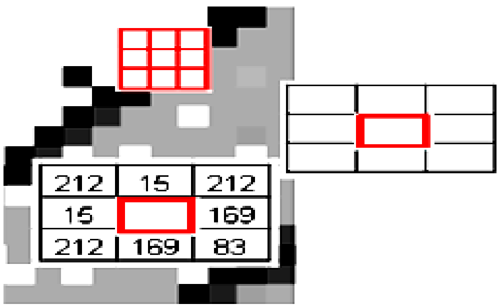
Mean Filter

Mean filtering is a linear filtering method for image smoothing. Its implementation is, as its name implies, intuitive and easy, i.e., it can reduce the amount of intensity variation between one pixel and the neighboring ones. The mean filter is the simplest type of low-pass filter because all of the coefficients of the mean filter have identical values. An example of a mean filter is shown in Figures 1 and 2. The idea is simply to replace each pixel value in an image with the mean value of its neighbors, including itself. The main purpose of doing this is to eliminate pixels which are unrepresentative of their surroundings [13], [14].

$1/9$	$1/9$	$1/9$
$1/9$	$1/9$	$1/9$
$1/9$	$1/9$	$1/9$

Figure 1. 3x3 Mean Filter/Kernel

Three factors can affect the characteristics of the filter (mask/kernel): width, height and shape of the filter. For example, the larger the size of the kernel, the more severe would be the smoothing result. Therefore, there is always a compromise between the reduction of noise and the blurring effects associated with the selection of filter size and type. A better filtering technique is needed for areas in an image that have fine details and edges so that these details are not lost in the filtering process [2]. Figure 2 shows an example of the standard mean filter and how the mean is computed to form the window pixels that replace the center pixel.



$$Mean = {(212 + 15 + 212 + 15 + 15 + 169 + 83)}\big/_{9} = 122$$

Figure 2. Example of Mean Filtering

Proposed Intelligent Mean Filter

The intelligent mean filter algorithm is an ordered statistical non-linear filter which combines the techniques of the traditional median filter and mean filter in order to achieve a better result. The median filter ranks the pixel values using the ascending order or descending order and picks the middle value or the median, which is applied by replacing the median or middle values with the center values in the activate region. However, no detection mechanism is used to test and verify whether or not the center value in the region is polluted.

In this proposed filter algorithm, an initial window is chosen as 2n+1, and then the pixel values in the window are arranged using some specified criteria. The pixel value before the median value, the median value and the pixel value after the median value are chosen, including the minimum and maximum values. The pixel value before the median value and the value after the median value are tested to find out if they are polluted or not. The test is conducted by comparing them to the minimum and maximum values. If the condition of the value before the median is equal to the minimum value, then the window size is increased. On the other hand, if the value after the median is equal to the maximum value, then the window size is increased, meaning that there is a very high likelihood of impulse noise being present in the window. Hence, the size of the window is increased in order to bring in more pixels that may not be polluted to aid in the filtering process. After the window size is increased, the entire process is carried out again. If the same situation occurs, or the same conditions are met, the window size is increased again until it reaches the maximum window size. If the two conditions are not met, then the two values appear to be noiseless pixel values, hence the intelligent mean is computed. This is done by adding the median value and the two values before the median and after the median and dividing it by the number of values.

The computation of the intelligent mean is quite complex and takes time. After this process, the difference between the individual pixel values and the intelligent mean is computed. These differences are compared to a threshold value. If the difference is less than the threshold value, then the pixel value associated with this is replaced by the intelligent mean. This process continues until all of the affected values are successfully replaced. Finally, the maximum value is also replaced by K if it is equal to 255 for an 8-bit image; it is, however, different for an image with a higher bit count.

The neighborhood pixel properties are carefully employed in choosing the window size, and the relationship involved is used to arrive at a useful algorithm. The moving-window architecture technique shown in Figure 3 is adapted from the adaptive median filtering technique to help in the implementation of this algorithm. This is a systematic technique that moves throughout the entire image from point to point and helps the filtering process to work in every window.

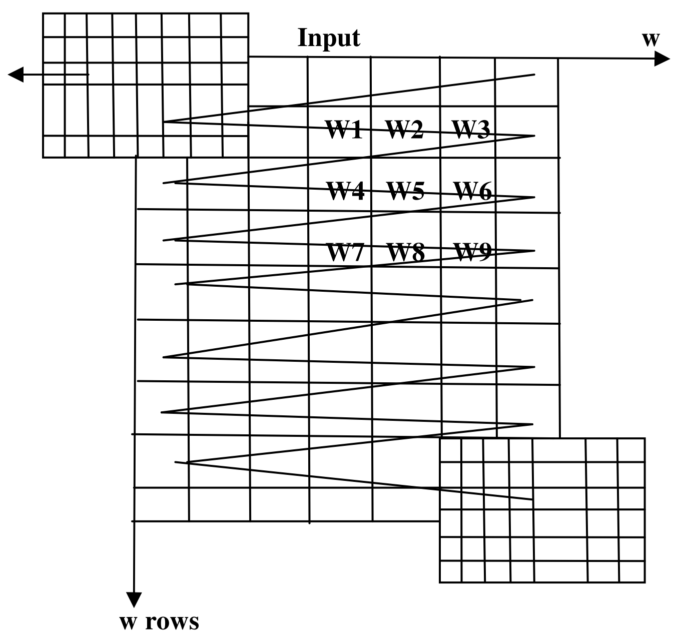


Figure 3. Moving-Window Architecture

For finding the arithmetic mean of a discrete set of numbers, a formula is applied, which is the same for finding the intelligent mean. If n numbers are picked, each distinct number is denoted by a_i, where $i = 1,\ldots,n$.

$$Mean = \frac{1}{n}\sum_{i=1}^{n} a_i \qquad (2)$$

Implementation and Testing of the Algorithm

K = median position in the sorted list
X_{med} = median of gray level value in $S_{x,y}$
X_{min} = minimum gray level value in $S_{x,y}$
X_{max} = maximum gray level value in $S_{x,y}$
X_{k-1} = value directly adjacent to the left of the median value
X_{k+1} = value directly adjacent to the right of the median value
$S_{x,y}$ = size of the window
D = largest interval between the sorted values starting for n=2 to n=n-1
K1 = pixel corrupted by impulse noise (salt noise) i.e., K1 = 0.
K2 = pixel corrupted by impulse noise (pepper noise) i.e., K2 = 255 for an 8-bit image

The modified median filtering algorithm works at three different levels, denoted as level A, B and C, as follows:

Level A:
$A1 = X_{k-1} - X_{min}$
$A2 = X_{k+1} - X_{max}$
If A1 > 0 and A2 < 0 Goto level B Else increase the window size.

Level B:

$$X_{maen} = \frac{X_{k-1} + X_{med} + X_{k=1}}{n}$$

$$B1 = \left|X_{i,j} - X_{mean}\right| < threshold$$

$$B2 = X_{\max} - 255$$

If B1 is true then replace $X_{i,j}$ with X_{mean} and proceed
If B2=0 the replace X_{max} with X_{max} — threshold

Figure 4 illustrates how the value to the immediate left of the median and the value to the immediate right of the median (when the values are arranged in ascending order horizontally) are tested for the presence of impulse noise. Figure 5 illustrates how the intelligent mean is computed and how the detected pixels that are corrupted with impulse noise are replaced with the intelligent mean.

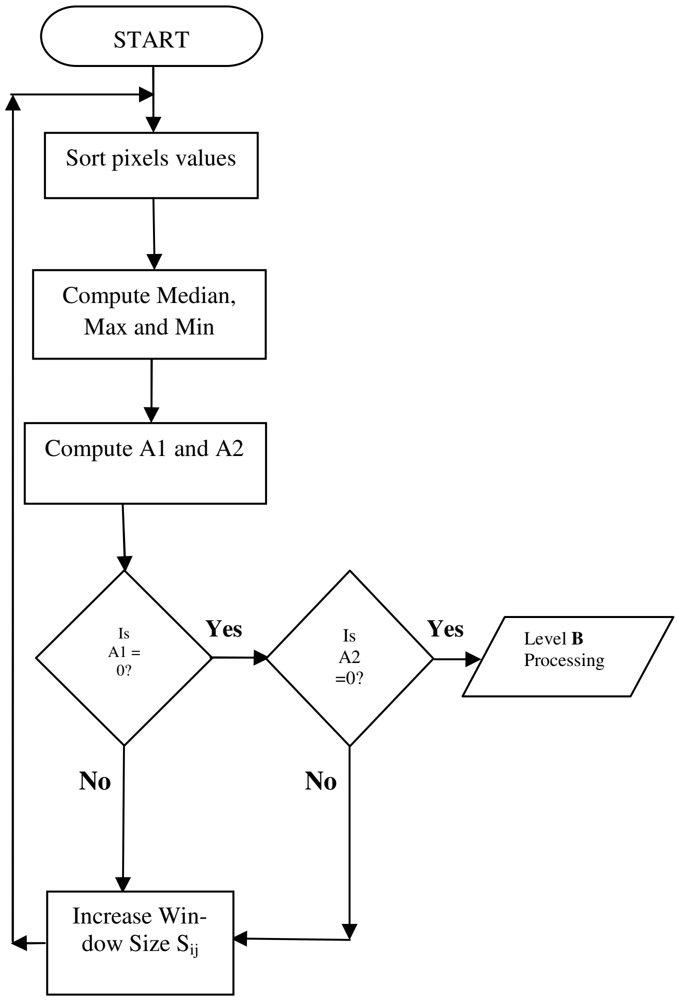


Figure 4. Flowchart Showing the Steps for the Detection of the Presence of Impulse Noise in the Active Window

Experimental Results

In order to test the performance rate of the proposed algorithm, experiments were performed at different noise levels. Intensive simulations were carried out on several images corrupted with impulse noise and Gaussian noise. The results showed that the modified efficient median filter achieved better results when applied to images corrupted by impulse noise (salt and pepper) than the results obtained from the image corrupted by Gaussian noise. The performance evaluation of the filtering operation was demonstrated by the output of the following images. The modified median filtering algorithm was implemented using MATLAB 7.40(R2007a), applied to a 3x3 window.

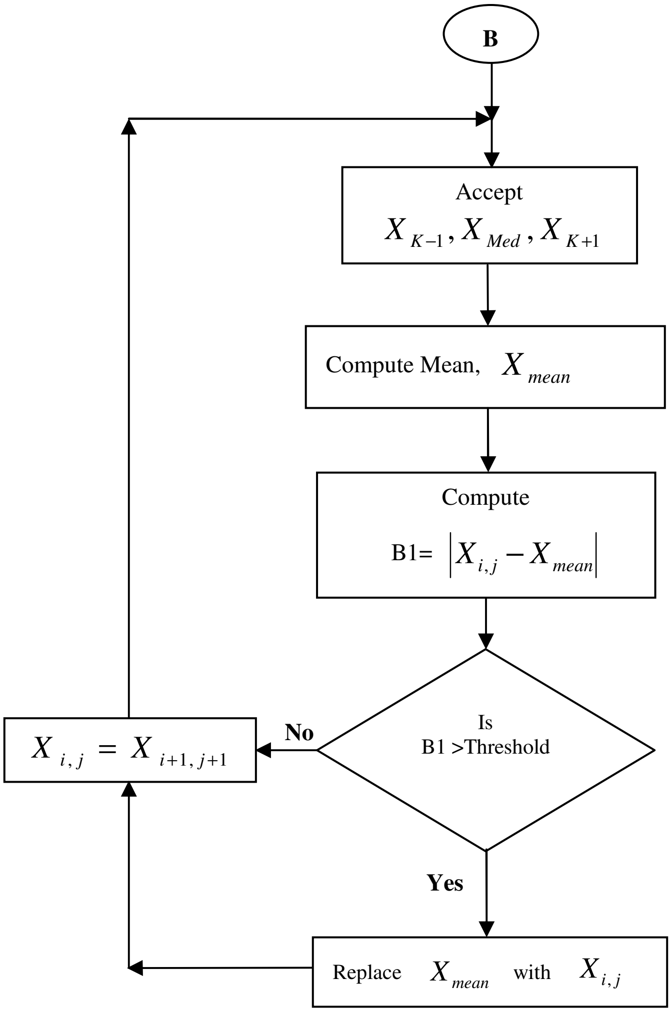


Figure 5. Flowchart Showing the Computational Steps of the Intelligent Mean Filter

Figure 6. Original Image of the Moon

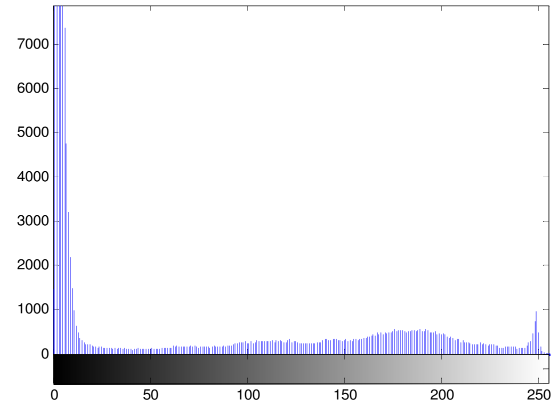


Figure 7. Histogram of the Original Image

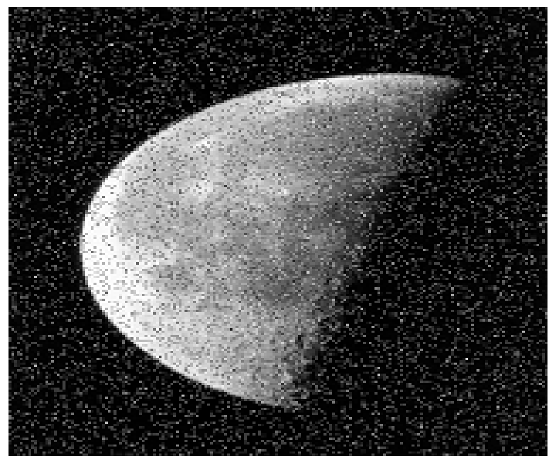


Figure 8. Image Polluted with 10% Impulse Noise

Figure 9. Filtered Image Using Intelligent Mean Filter

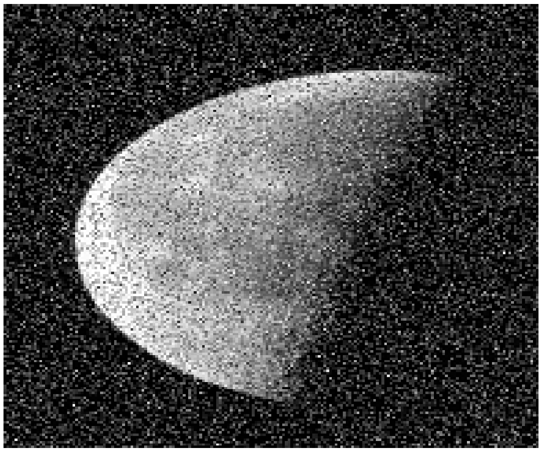


Figure 10. Image Polluted with 20% Impulse Noise

Figure 11. Filtered Image Using Intelligent Mean Filter

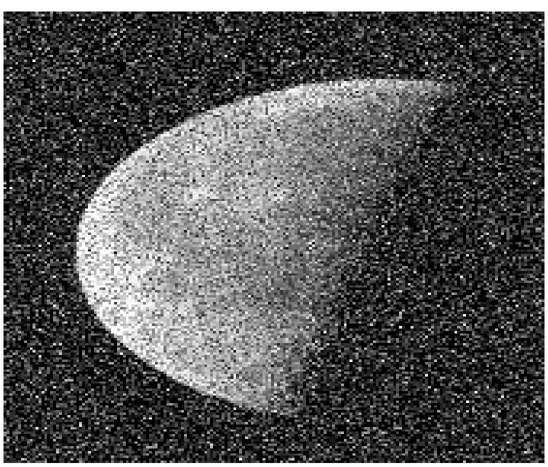


Figure 12. Image Polluted with 30% Impulse Noise

Figure 13. Filtered Image Using Intelligent Mean Filter

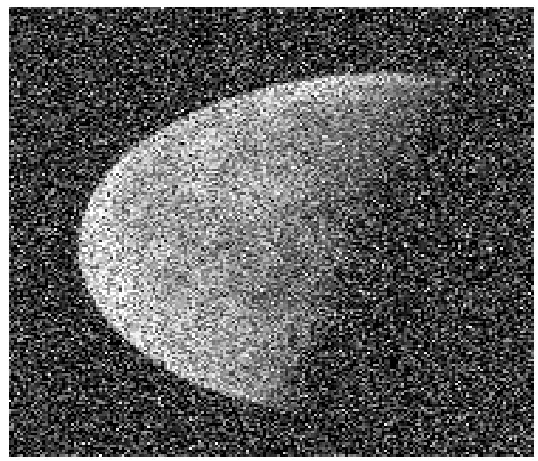


Figure 14. Image Polluted with 40% Impulse Noise

Figure 15.Filtered Image Using Intelligent Mean Filter

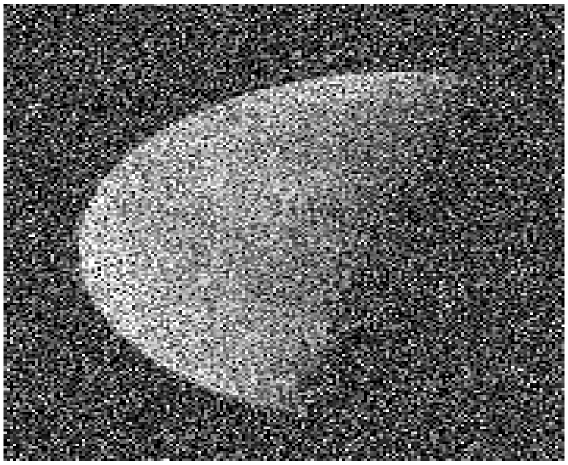


Figure 16. Image Polluted with 50% Impulse Noise

Figure 17. Filtered Image Using Intelligent Mean Filter

The original 2D grayscale 8-bit image of the moon is shown in Figure 6. The image is loaded and display using Matlab without noise added to it. Figures 8, 10, 12, 14 and 16 are the moon image corrupted with 10%, 20%, 30%, 40% and 50% salt-and-pepper noise, respectively. To show the efficiency and measure the effectiveness of the intelligent mean, the technique was applied to these corrupted images in order to produce the filtered images shown in Figures 9, 11, 13, 15 and 17. The images produced by the application of the intelligent mean clearly show that, pictorially, the noise added to the image was eliminated or significantly reduced. Figure 7 shows the distribution of the pixels in the image.

Simulation Results

Intensive simulations were carried out using several images of the moon, corrupted with various levels of impulse noise. The performance of the filtering operation was quantified using the Peak Signal-to-Noise Ratio (PSNR). The PSNR was chosen because it is one of the best known techniques for assessing the amount of noise pollution in an image and also the amount of noise that is left in a filtered image. The peak signal-to-noise criterion was adopted in order to measure quantitatively the performance of various digital filtering techniques [12]. This PSNR is defined as:

$$PSNR = 10 \log_{10}\left(\frac{255^2}{MSE}\right) \tag{3}$$

where

$$MSE = \frac{1}{MN}\sum_{j=1}^{M}\sum_{i=1}^{N}\left(G(i, j) - F(i, j)\right)^2 \tag{4}$$

and where M and N are the total number of pixels in the column and row of the image, respectively, and G denotes the noise image and F denotes the filtered image.

Table 1. Peak Signal-to-Noise Ratio of the Filtering Techniques

Filter Methods	10% Impulse Noise	20% Impulse Noise	30% Impulse Noise	40% Impulse Noise	50% Impulse Noise
Mean Filter	33.70dB	31.97dB	29.95dB	29.28dB	28.70dB
Standard Median Filter	34.35dB	32.63dB	31.39dB	30.45dB	29.67dB
Gaussian Filter	33.83dB	32.00dB	30.84dB	29.96dB	29.29dB
Adaptive Weiner Filter	33.79dB	31.98dB	30.83dB	29.95dB	29.28dB
Proposed Intelli-gent Mean	38.67dB	36.93dB	35.45dB	34.02dB	32.95dB

Conclusion

In this study, the authors proposed an intelligent mean filter, designed and implemented using MATLAB. The method is a very simple non-linear filter, compared to other filters, and is easier to implement in terms of noise detection and noise signal suppression. It employs a moving-window architecture that moves through the image pixels in an overlapping manner and filters the signal based on the computation of the intelligent mean per window.

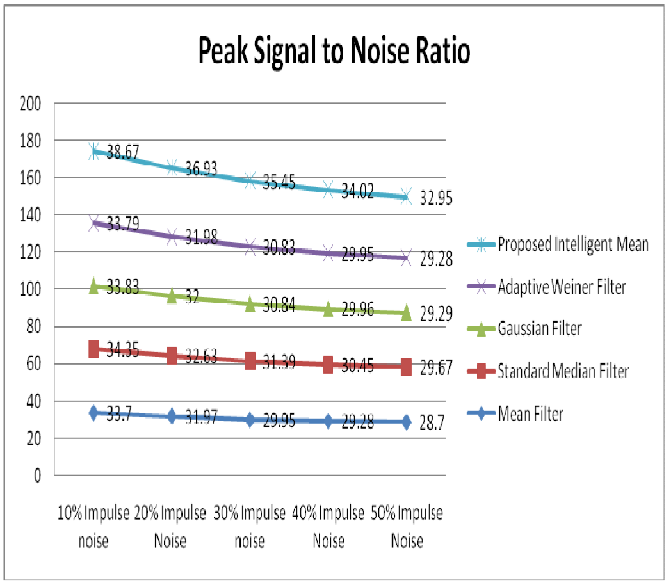


Figure 18. Graphical Representation of the Result of the Peak Signal-to-Noise Ratio in the Filtering Techniques

Extensive simulation experiments were conducted on the moon image with different levels of noise in order to compare the proposed intelligent mean technique with several other filtering techniques. The simulation results quantitatively showed that the proposed algorithm performed better than many existing state-of-the-art techniques in terms of preserving fine details of the image and drastically reducing the image noise factor.

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