International Journal of Computer Applications (0975 – 8887)
National Conference on Recent advances in Wireless Communication and Artificial Intelligence (RAWCAI-2014)

# Comparative Analysis of Median Filter and Adaptive Filter for Impulse Noise – A Review

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## ABSTRACT
In this paper a comparative analysis to the problem of impulse noise reduction in grey scale image is presented. The basic idea behind this analysis is the maximization of the similarities between pixels in a predefined filtering window. The comparison introduced to this median filter and adaptive filter lies in the establishment of parameters of the similarity function and hence further improvement is possible in adaptive filter and also adapts itself the fraction of corrupted image pixels. The improved adaptive filter preserves edges, corners and fine image details, is relatively fast and easy to implement as compared to median filter. The results show that the adaptive filter outperforms most of the basic algorithms for the reduction of impulsive noise in grey scale images..

## General Terms
Image Processing, Filter, Algorithms.

## Keywords
PSNR, MSE, Median Filter, Adaptive filter, Image processing with grey scale images

## 1. INTRODUCTION
Generally one of the most common problems encountered in image acquisition and/or transmission is the contamination of the image by impulse noise due to various imperfections in image sensors and communication media. The noise in the image data severely degrades the performance of further table word processor formats for your particular conference. Image processing operations (such as edge detection, image segmentation, object recognition, etc.) that are to be performed on the acquired/received image data. Therefore, it is of vital importance to restore the corruptions in the image data caused by the noise before performing any subsequent image processing task on the image data. In the last decade, a large number of methods have been presented for the removal of impulse noise from digital images. A considerable number of these methods are based on order statistics filters, which exploit the rank order information of the pixels contained in a given filtering window. The *standard median filter* [2] attempts to remove impulse noise from the center pixel of a given filtering window by altering this pixel with the median of the pixels within the window. This simple approach has the advantage of being computationally very efficient and provides a noise removal performance but it also has the disadvantage of removing thin line sand blurring image details even at low noise densities. The modified versions of the standard median filter, the *weighted median filter* [3] and the *center- weighted median filter* [4], which give more weight to certain pixels in the filtering window, have been proposed to avoid the inherent drawbacks of the standard median filter. These filters usually offer better detail preservation performance than the median filter, but at the expense of reduced noise removal performance. The standard, the weighted and the center-weighted median filters are *spatially invariant* operators making no distinction between the noisy and the noise-free pixels of the input image regarding filtering behavior. This results in undesirable distortions and blurring in the output image and also causes the loss of valuable information from the image data. In an attempt to avoid this problem, a number of methods [20–42] combine the noise filter with an *impulse detector* that aims to determine whether the center pixel of a given filtering window is noisy or not. If the center pixel is classified by the impulse detector as a noisy pixel, its restored value is obtained by processing the pixels in the filtering window by the filter. If the center pixel is classified as noise free, it is left unchanged. Although this approach significantly enhances the performance of the noise filter by reducing its distortion effects, its performance inherently depends on the performance of the impulse detector. Hence, several different impulse detection approaches utilizing median filters [4–7,20-25], center-weighted median filters [3-4][24–27], Boolean filters [28], edge detection kernels [29], homogeneity level information [30], statistical tests [31,32], classifier based methods [33], rule based methods [34], level detection methods [35], pixel counting methods [36] and soft computing methods [37–40] have been proposed. In addition to the median based filters mentioned above, various types of mean filters are successfully utilized for impulse noise removal from digital images [41–44]. These filters usually exhibit better filtering performance compared to the median-based filters. However, their computational complexity is, in general, higher too. There are also a number of non linear filters based on soft computing methodologies such as neural networks [45, 46], fuzzy systems [47–51] and neuron fuzzy systems [52–56] as well as many hybrid filters [56–65] constructed by combining the desired properties of the above mentioned filters. These filters are usually more complex than the above mentioned median and the mean based filters, but they usually offer much better noise suppression and detail preservation performance. Naturally, none of the impulse noise removal methods mentioned above is 100% efficient. They leave some of the noisy input pixels unfiltered, causing noise spikes at the output image, and filter some of the noise-free pixels, causing undesirable distortions at the output image. This is mainly due to the uncertainty introduced by the noise corrupting the input image. In the last few decades, fuzzy systems have been shown to be very successful at handling uncertainty and imprecision in many different problems encountered in various areas of science and technology. Hence, fuzzy systems may be employed to deal with the uncertainty encountered in impulse noise removal from digital images and may be used to improve the performances of impulse noise filters provided that appropriate network topologies and processing strategies are adopted. In this paper, a comparative

filtering approach for improving the performances of image impulse noise filters is proposed. The analysis exploits the fact that the output image of a adaptive image filter varies depending on the standard parameters of the input image. Hence, the comparative analysis generates the best noise free image by processing these images in the adaptive filter, computes the enhanced output image from these noisy images by using a fuzzy system and also compares the median filter and adaptive filter in terms of standard parameter such as PSNR, MSE, etc. The validity of the analysis has been demonstrated by extensive simulation experiments covering different impulse noise filters. The rest of the paper is organized as follows: Section 2 explains the motivation behind the analysis, describes the building blocks used to implement it and literature survey. Section3 discusses the comparative analysis with selected impulse noise filters from the literature. Results of the comparative filtering experiments conducted to evaluate the performance improvements obtained by using the adaptive filter method and comparative discussion of these results are also presented in this section. Section4, which is the final section, presents the conclusions..

## 2. LITERATURE SURVEY

There exist different filters for impulse noise removal from images. Linear filters such as averaging filters do good noise filtering to some extent, but produces blurring effect on the restored images. Non linear filters such as median filters are popular techniques for removing impulse noise because of its good denoising power and computational efficiency [1-6]. Median filters (MED) replace the value of a pixel by a median of the intensity levels in the neighborhood of that pixel. Median filters use a fixed filtering window size for finding out neighborhood pixels. However most of the median filters are implemented uniformly across the image and thus tend to modify both noisy and noise free pixels. So there is a chance of replacement of good pixels by some corrupted ones. Consequently denoising is often accomplished at the expense of blurred and distorted features thus removing fine details in the image. There are different variations of median filters such as weighted median filters (WM) [4], center weighted median filters (CWM) [3] and adaptive median filters (AMED) [9]. An adaptive median filter discriminates pixels in the filtering window as corrupted and uncorrupted and then a filtering technique is applied to corrupted pixels in the window. In this method noisy pixels are replaced by the median value of the pixels in the filtering window. AMED [9] performs well at low noise densities since the corrupted pixels that are replaced by the median values are very few. At higher noise densities, window size has to be increased to get better noise removal which will lead to less correlation between corrupted pixel values and replaced median pixel values. In efficient decision-based algorithm (EDBA) [10], the corrupted pixels are replaced by either the median pixel or neighborhood pixel by using a fixed window size of 3x3 resulting in lower processing time and good edge preservation. EDBA filter [10] performs well only for salt and pepper noises up to 70%. In this method, a smooth transition between the pixels is lost leading to degradation in the visual quality of the image in the form of line artifacts, since it only considers the left neighborhood from the last processed value. The directional weighted median filter (DWM) [11] uses a direction based approach for filtering out impulse noise from noisy images. DWM impulse detector makes use of the differences between the current pixel and its neighbors aligned with four main directions in a filtering window of size 5 to detect noisy pixel positions. After detection, noisy pixels identified are replaced by outputs of weighted median filter. This method uses the information of the four directions to weight the pixels in the filtering window. A hybrid method, combining fuzzy approach and directional weighted median method FBDWM [12] consists of two noise detection modules and a fuzzy filtering module for uniform impulse noise detection and reduction. Noise detection modules are based on fuzzy logic and four main directions whereas fuzzy filtering module utilizes the directional weighted median. But both the methods work well only in the case of low density impulse noises. Switching median filters are shown to be simple and yet more effective than uniformly applied methods such as median filters [13]. They perform noise filtering as a two stage process – detection and filtering. During detection stage, it will identify the possible noisy pixels in the image and then filtering algorithm is applied to replace noisy pixels. Usually noisy pixel replacements in switching median filters are done by using median filters and its variants. The efficiency of a switching median filter heavily depends on the efficiency of detection algorithm used. The earlier developed switching median filters were commonly found, being non adaptive to a given, but unknown, noise density and prone to yielding pixel misclassifications especially at higher noise density interference. There are different methods for impulse noise detection fuzzy approaches as in [14–17], neural approaches [17] and boundary based approaches [18]. Among the three categories boundary based approach [18] is preferred due to its simplicity compared to computational complexity and system structure of other two categories. To address pixel misclassification issue in switching median filters at high density noise, a noise adaptive soft switching median filter (NASM) was proposed [19], which consists of a three level hierarchical soft switching process. The boundary based approach called boundary discriminative noise detection [18] is very good in detecting impulse noises of various densities. BDND [18] can handle image corruption even up to 90% noise density. Highly effective impulse noise reduction algorithm [20] provides an efficient method for noise detection. This method uses both boundary based information and directional based information for detection purpose. This method is more efficient in noise detection than BDND method in terms of false alarms and misdetection produced. The detection scheme used in Noise Adaptive Fuzzy Switching Median Filter (NAFSMF) [21] uses a histogram based approach for detection. In this method, the two peaks in the image histogram that corresponds to noisy pixel values are identified by traversing histogram from both sides. In noisy pixel replacement stage many median based schemes have been proposed. The NASM [19] noise replacement strategy gives robust performance in removing impulse noise while preserving signal details across a wide range of noise densities, ranging from 10% to 50%. However, for those corrupted images with noise density greater than 50%, the quality of the recovered images become significantly degraded, due to the sharply increased number of misclassified pixels. NAFSMF [21] uses fuzzy membership value of luminance difference value and median value in the filtering window for noisy pixel replacement. The noisy pixels are replaced either partially or fully depending on fuzzy membership value. The MNASM [18] is modified with BDND detector which gives better performance for high density impulse noises as compared to filtering in NASM [19] but this modified NASM also causes blurring of edges and loss of finer details in the image. Due to this blurred edges and finer details further improvement is required in Adaptive filters.

# 3. COMPARATIVE ANALYSIS

For the objective measurement of any filter for image processing, there are various parameters [67, 68] on the basis of which performances of the filtered images are evaluated. The peak signal to noise ratio is one of the parameter which gives best comparative analysis among others because Peak Signal to Noise Ratio [67] should be as large as possible which means that the content of signal in the output is large and the noise is less. Since it is peak signal to noise ratio that's why the value of the signal is considered as maximum which is 255 (for gray scale images the gray scale ranges from 0 – 255) and give the noise is less in images.

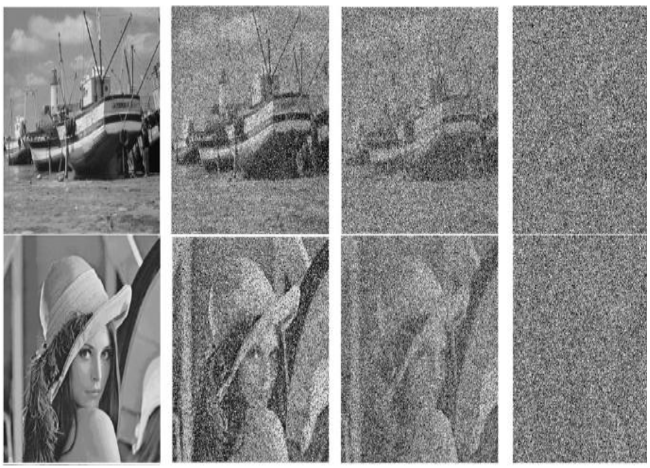
$$PSNR = 10log_{10}\frac{255^2}{MSE}$$

In this equation MSE [68] is mean square error that should be less, which means that the pixel intensity of the input and output image should be as close as possible.

$$MSE = \frac{1}{MN}\sum_{j-1}^{M}\sum_{k-1}^{N}\left(x_{j,k} - x'_{j,k}\right)^2$$

Where, *M* and *N* are rows and columns, respectively of the

image. Where $x_{j,k}$ is the original image and , $x'_{j.k}$ is the corresponding output image. Here Figure 1 shows corrupted boat and lena images with 30%, 60% and 90% noise. In table 1 and table 2 shows the calculated PSNR [67] value for adaptive filters comparable with other median filters, which is essential for noise free image. From these corrupted images, PSNR [67] parameters and graph we analyze that adaptive filters give better results as compare to the median filter because in table 1 and table 2 for boat and lena images PSNR [67] value of adaptive filters produces large value as compare to the other median filters and also in graph figure 2 and figyre 3 gives best result. So we can say that adaptive filters produces best results whether images are corrupted by 30%, 60% and 90% as compare to other median filters.



(a) (b) (c) (d)

**Figure 1: Column a represents original Boat and Lena images. Columns b, c and d represent Boat and Lena images corrupted with 30%, 60%, and 90% noise, respectively**

**Table 1: PSNR values obtained for Boat image**

| Noise (%) | MED | AMED | MNASM | EDBA | HMNASM | DAWSM |
|---|---|---|---|---|---|---|
| 90 | 8.381632 | 10.3233 | 22.4115 | 18.37734 | 22.69966 | 23.5532 |
| 80 | 12.71335 | 15.46635 | 23.6205 | 21.12903 | 23.91824 | 25.2724 |
| 70 | 17.37563 | 20.96976 | 24.6718 | 23.53234 | 24.85212 | 26.7972 |
| 60 | 20.43905 | 25.03024 | 25.9988 | 25.36471 | 26.12361 | 28.1546 |
| 50 | 21.72098 | 27.13025 | 27.5804 | 27.26044 | 27.82047 | 29.4368 |
| 40 | 22.60334 | 2.52717 | 29.6215 | 29.03983 | 30.303 | 31.0387 |
| 30 | 23.21251 | 30.40575 | 31.903 | 31.36166 | 32.58421 | 33.1582 |
| 20 | 24.06188 | 32.21128 | 34.4342 | 33.76107 | 35.27393 | 35.2341 |
| 10 | 24.9179 | 33.9189 | 37.9189 | 37.47399 | 38.59112 | 39.0306 |

**Table 2: PSNR values obtained for Lena image**

| Noise (%) | MED | AMED | MNASM | HMNASM | DAWSM |
|---|---|---|---|---|---|
| 90 | 8.766 | 10.647 | 24.716 | 25.218 | 26.2065 |
| 80 | 13.33 | 16.053 | 26.697 | 26.981 | 28.1711 |
| 70 | 18.53 | 21.924 | 28.065 | 28.334 | 29.6707 |
| 60 | 22.14 | 27.23 | 29.506 | 29.762 | 31.3021 |
| 50 | 23.65 | 30.09 | 31.355 | 31.708 | 32.8273 |
| 40 | 24.51 | 31.793 | 33.847 | 34.117 | 34.5199 |
| 30 | 25.48 | 33.85 | 36.142 | 36.5 | 36.7011 |
| 20 | 27 | 35.97 | 38.701 | 39.225 | 38.9088 |
| 10 | 28.47 | 38.18 | 42.586 | 42.942 | 42.9264 |

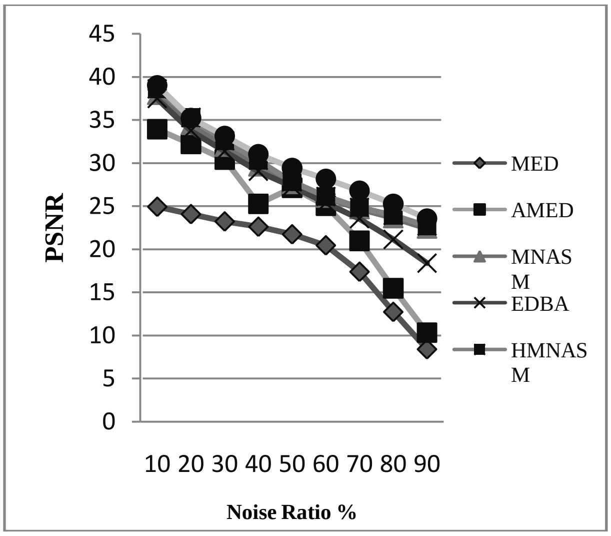



**Figure 2: Graph representing the performance measures obtained after the applying the different filters on the corrupted Boat image**

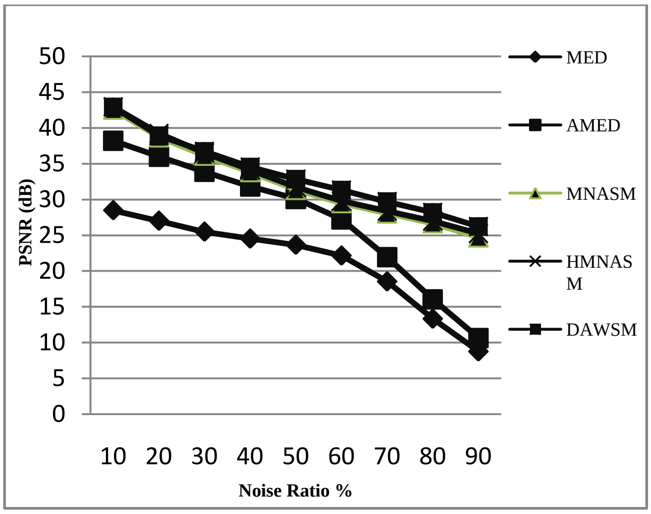



**Figure 3: Graph representing the performance measures PSNR obtained after the applying the different filters on the corrupted Lena image**

## 4. CONCLUSION

In this paper, we analyze that images that are corrupted with high density of impulse noises based on different PSNR values. Adaptive filtering is an improved filtering technique as compare to median filter in which the filtering is applied only to corrupted pixels in the image while the uncorrupted pixels are left unchanged. The Adaptive filtering approach is used to reduce the number of noisy pixels during filtering. The advantage of Adaptive filter is that it is retaining the edge information in the case of high density impulse noises. The Adaptive filter is found to be retaining finer details in the image and the images restored are with an improved visual quality. The detail preservation ability of the adaptive filter makes it suitable for medical image denoising, where also detail preservation is an important issue.

## 5. FUTURE SCOPE

In Future the adaptive algorithm can be improved for removing the image noise completely without visible distortion. The main techniques we involved for this improvement are (1) adaptive noise detection, (2) non-linear filter. For this adaptive processing, three parameters with MSE, local background and PSNR can further improve as for adaptive functions. The PSNR and MSE can be dynamically modified according to local image features. These improved adaptive filters when compared with other linear and non linear filters can give best noise free images because linear filters produces blurred image and very complex to design but when we compare with other well known non linear median algorithms, the filtering efficiency can be highest due to lower complexity and can be higher noise reduction ratio, particularly for filtering high noise images. Furthermore, the computational complexity of the improved algorithm can be quite low, and so this improved adaptive filter will be very appropriate for a VLSI chip implementation in real-time systems. Therefore, this adaptive approach can be able to provide better performance- complexity tradeoffs for video noise reduction and morphological operations [69] in real-time applications.

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