International Journal of Electronics and Communication Engineering.
ISSN 0974-2166 Volume 5, Number 1 (2012), pp. 85-97

http://www.irphouse.com

Improving the Effectiveness of the Median Filter

Kwame Osei Boateng[1], Benjamin Weyori Asubam[1,2] and David Sanka Laar[2]

[1]Kwame Nkrumah University of Science and Technology, Ghana
E-mail: boat.soe@knust.edu.gh
[2]University for Development Studies, Ghana
E-mail: weyoribenjamin@yahoo.co.uk, kontilaar@yahoo.co.uk

Abstract

Digital images are often corrupted by Impulse noise due to errors generated in noisy sensor, errors that occur in the process of converting signals from analog-to-digital and also errors that are generated in the communication channels. This error that occurs inevitably alters some of the pixels intensity while some of the pixels remain unchanged. In order to remove impulse noise and enhance the affected image quality, we have studied the median filter and are proposing a method based on an improved median filtering algorithm. This method removes or effectively suppresses the impulse noise in the image whiles preserving the image edges information and enhancing the image quality. The proposed method is a spatial domain approach and uses the overlapping window to filter the signal based on the selection of an effective median per window. The approach chosen in this work is based on a functional level 2n +1 window that makes the selection of the normal median easier, since the number of elements in the window is odd. The median so chosen is confirmed as the effective median or, where the median is an impulse a more representative value is sought and used as the effective median. The performance of the proposed effective median filter has been evaluated in MATLAB simulations on an image that has been subjected to various degrees of corruption with impulse noise. The results demonstrate the effectiveness of our algorithm vis-à-vis the standard and adaptive median filtering algorithms.

Introduction

Image Processing is one of the rapidly and fast growing fields in the area of computer science and engineering. The growth of this field has been improved by the technological advances in digital computing, computer processors, digital signal processing and mass storage devices. All fields which were operating on the traditionally analog imaging are now gradually switching to the digital systems for their ease of use, affordability and flexibility. Image processing is very useful and has been extensively used in the area of medicine, film and video production, photography, remote sensing, desktop publishing, military target analysis, and manufacturing automation and control [1][2]. The various applications, such as those mentioned, usually require bright and clear images or pictures, hence corrupted or degraded images need to be processed to enhance easy identification and further works on the image. Image processing techniques such as image enhancement, object detection and image filtering are used to process the image depending on the type of interference that has caused the degradation factor.

Filtering is an essential part of any signal processing system which involves estimation of a signal degraded in most cases by impulse noise which is mostly caused by the error generated when converting an analog signal to a digital signal using the analog-to-digital converter. Several filtering techniques have been developed over the years for various applications. The type of noise factor and intensity of the noise that has corrupted the image is also taken in to account before the filter is developed and used.

Digital image filtering techniques can be categorized into two broad areas; spatial domain filtering and frequency domain filtering. The spatial domain filtering techniques are based on the direct manipulation of the image pixels whiles the frequency domain filtering techniques has to do with modifying the Fourier transform of the image.

The spatial domain nonlinear filtering techniques are preferred in the presence of impulse noise (salt and pepper), since they can cope well with the nonlinearities of the image formation model and also takes into account the nonlinear nature of the human visual system [3]. Order statistic filters are nonlinear spatial filters whose response is based on ordering (ranking) the pixels contained in the image area encompassed by the filter and then replacing the value of the center pixel with that value determined by the ranking result [4]. The best known order-statistic nonlinear filter is the median filter.

A large number of methods have been proposed to remove impulse noise from digital images. The Standard median filter and mean filter are used to reduce salt-pepper noise and Gaussian noise respectively. When these two noises exist in the image at the same time, use of only one filter method cannot achieve the desired result [12]. The standard median filter [5] is a simple rank selection filter that attempts to remove impulse noise by changing the luminance value of the center pixel of the filtering window with the median of the luminance values of the pixels contained within the window. Although the median filter is simple and provides a reasonable noise removal performance, it removes thin lines and blurs image details even at low noise densities. The weighted median filter [6] and the center-weighted median filter [7] are modified median filters that give more weight to the appropriate pixels of the filtering window. These filters have been proposed to avoid the inherent drawbacks of the standard median filter by controlling the tradeoff between the noise suppression and detail preservation.

The switching median filter is obtained by combining the median filter with an impulse detector. The impulse detector aims to determine whether the center pixel of a given filtering window is corrupted or not. If the center pixel is identified by the detector as a corrupted pixel, then it is replaced with the output of the median filter, otherwise, it is left unchanged [8] [9] [10]. In the case where majority of the edge pixels in the image are polluted by impulse noise, filtering is incomplete because the switching median filter only works on the centre value of the window and even for the smallest sized window, 3×3, it is not possible to have an edge pixel in the centre of the sliding window.

Adaptive Median Filter (AMF) is designed to eliminate the problems faced by the Standard Median Filter [5]. Adaptive Filter (AF) changes its behavior based on the statistical characteristics of the image inside the filter window. Adaptive filter performance is usually superior to non-adaptive counterparts. The improved performance is at the cost of added filter complexity. Mean and variance are two important statistical measures based on which adaptive filters can be designed [11]. In practice this filter imposes a limit to the window size, $S_{xy.}$ When this limit is reached while the selected median is an impulse, the impulsive noise remains in that window of the image. The adaptive median filter achieves good results in most cases, but even so, computation time is proportional to the degree of corruption of the image being filtered.

In this work we propose a spatial domain approach using the overlapping window to filter the signal based on the selection of an *effective* median per window position. For each window position a median is found for all pixels in the window. The median is tested, and if it is unaffected by impulse noise, it is confirmed as the *effective median*, otherwise a more representative value is sought and used as the *effective median*.

This paper is organized as follows; Section 2 discusses the impulse noise removal technique using standard median and some of its derivative filters and their implementations. Section 3 presents the proposed effective median filtering technique and its implementation. An illustration using one window position in the proposed technique is presented in Section 4. Experimental results are shown in Section 5 and finally the paper is concluded in Section 6.

The Median Filtering Algorithm

In this section, we present a brief review of the standard median filtering algorithm.

The median filter is a non-linear ordered statistic digital filtering technique which is normally used to reduce noise drastically in an image. It is one of the best windowing operators out of the many windowing operators like the mean filter, min and max filter and the mode filter. The simple idea is to examine a sample value of the input signal and decide if it is representative of the signal. Due to this, the median filter often does a better job than the boxcar filtering technique with regard to preserving useful detail in an image [13].

The median filter filters each pixel in the image in turn and its nearby neighbours are used to decide whether or not it is representative of its surroundings. Normally, instead of replacing the pixel value with the mean of neighboring pixel values, median filter replaces it with the median of those values. That is, the values from the surrounding neighbourhood are first sorted into numerical order, and then the value of the pixel in question is replaced with the middle (median) pixel value. The neighbourhood is referred to as the *window*. The window can have various shapes centred on the target pixel. The square is a typical shape chosen for windows defined for 2D images. It should be noted that under normal circumstances the median filter, is performed using a window containing an odd number of pixels. If the neighbourhood under consideration consists of an even number of pixels, the median value selected as the output is the average of the two middle pixel values. The figure below illustrates an example of how the median filter calculation is performed in the window.

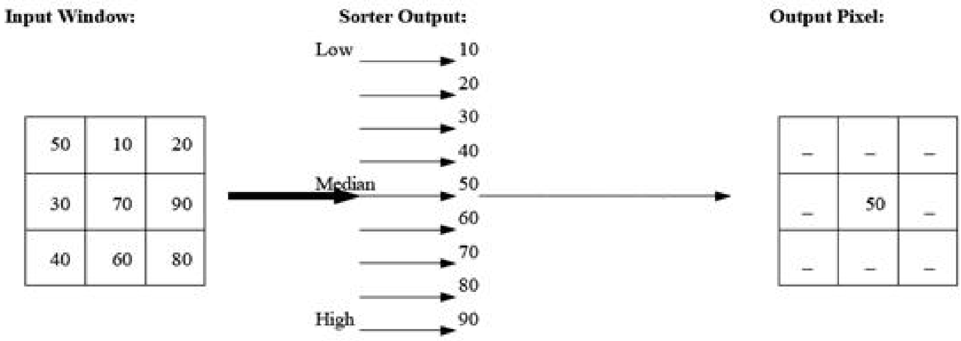


Figure 1: A graphical depiction of the median filter operation

This filter works by analyzing the neighborhood of pixels around an origin pixel like in the diagram above, for every valid pixel in an image. For this case, a 3×3 window, of pixels is used to calculate the output. For every pixel in the image, the window of neighboring pixels is found. As shown in the example above, the pixel values in the window are sorted in ascending order and the median value is chosen, in this case the median value is 50. Next, the pixel in the output image corresponding to the origin pixel in the input image is replaced with the value specified by the filter order. The value in the origin which is 70 is replaced by 50.

One of the advantages of median filter over the other rank order filters especially the mean filter, is that the median value is a more robust average than the mean value; the median value will not be affected significantly by one very unrepresentative pixel in neighbourhood. The median value of the surrounding pixels is most likely to be the value of one of the pixels in the neighbourhood within the window. Thus the median filter is least likely to create new unrealistic pixel values especially when the filter is working in transition zones. For this reason, the median filtering technique is much better than the mean filtering technique in terms of preserving sharp edges [14].

An important shortcoming of the median filter is that its output is always constrained, by definition, to be the median value in the window. In an k×k window, if the number of polluted pixels is greater than the value $\left(\frac{k\times k}{2}\right)$, then the median computed will be an impulse and the noise will not be removed. On the other hand the centre value replaced is not tested to find out if it is an impulse or not. Hence if it is not an impulse but a fine pixel of the image then it is removed unnecessarily. The median filter performs poorly when the intensity of the noise is high.

Proposed Effective Median Filter

In the proposed method the size of the window is fixed, however, the (effective) median may be different from the value at the middle of the sorted pixel values. The proposed effective median filter is designed to diminish the problem faced by the standard median filter and reduced by the adaptive median filter. As with the standard median technique, the window is chosen to cover a $k \times k$ array of pixels such that

$$k^2 = 2n + 1 \Rightarrow n = \frac{k^2-1}{2}$$

where for integer $n > 0$, $k = 3, 5, 7, \ldots$. In the proposed technique of filtering, as in standard median filter, the pixels are sorted and the median is selected from a sorted list of the current window.

From this point processing is partitioned into three stages, which we call levels A, B and C processing, respectively. The minimum pixel value, X_{min}, and the maximum pixel value, X_{max}, are compare with impulse values K1 and K2, respectively, where K1=0 and K2=255. If X_{min} = K1 or if X_{max} = K2 then the window has impulse noise and processing proceeds through all Levels A, B, and C. Otherwise processing proceeds through only Level C. (See Figure 2.)

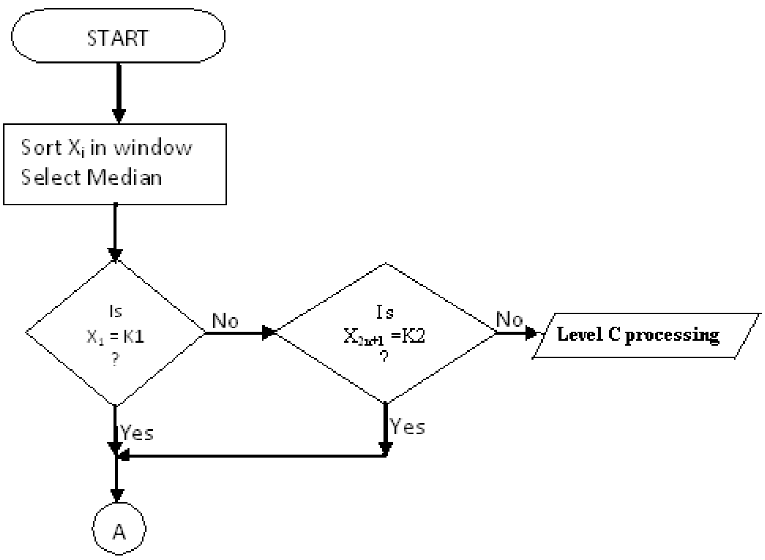


Figure 2: Checking window for presence of impulse noise.

Level A Processing

The selected median value is tested to verify if it is an impulse or not. If the median value is equal to the minimum or maximum value, then it is deemed to be an impulse. In this case a pixel with its value between the minimum and maximum values is searched for, starting from the immediate neighborhood of the median position. When it is realized that all pixels in the window are impulses the median is computed as follows:.

$$X_{med} = \frac{K1+K2}{4}$$

where X_{med} is the median. The selected or computed median value, X_{med}, is referred to as the *effective median* in this work.

The flow chart of this level of processing is shown in Figures 3.

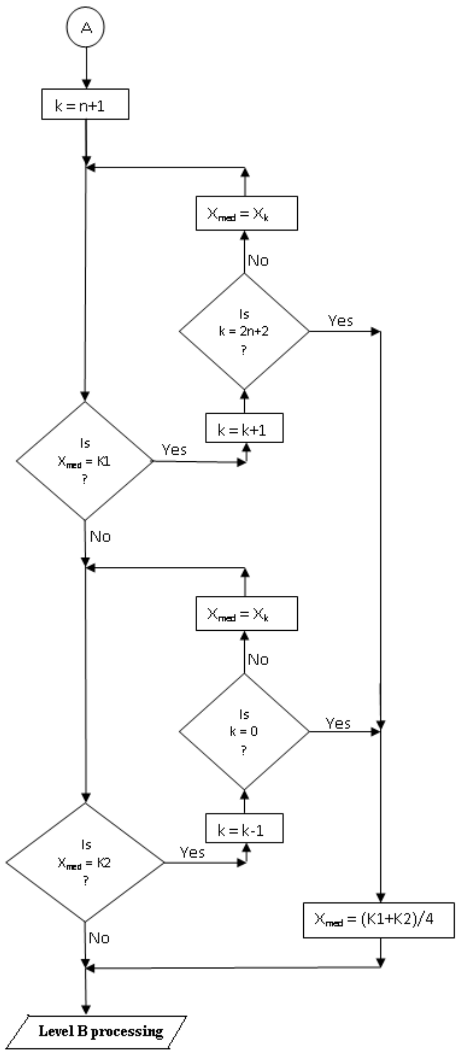


Figure 3: Level A processing.

Level B Processing
Impulse noise is removed at this level. All pixels in the window are inspected and any that are impulses are replaced with the median value. Next pixels in the window are re-sorted and proceed to Level C Processing stage.

Level C Processing
At this level distortions, if present, are removed. Processing at this level is always performed—even when no impulse noise is detected in current window position. Processing starts with the differences w_i being computed thus

$$w_i = X_{i+2} - X_{i+1}$$

for $i = 1, 2, \dots, 2n - 2$.

Next,

$$D = \max_{1 \le i \le 2n-2} w_i$$

is evaluated followed by the following computations for values at the extreme ends of the sorted list at this stage of processing:

$$X_1 = \begin{cases} X_{med}, if\ X_2 - X_1 > D \\ X_1, Otherwise \end{cases}$$

$$X_{2n+1} = \begin{cases} X_{med}, if\ X_{2n+1} - X_{2n} > D \\ X_{2n+1}, Otherwise \end{cases}$$

An Illustration of Effective Median Filtering

Assume the current window is as shown in Figure 4. Two pixels in the window has been corrupted by impulse noise. These are the values 0 and 255.

0	50	2
90	255	70
80	60	250

Figure 4: A noisy window.

Values in the window are sorted in ascending order top-to-bottom. The median value 70 is picked from the values in the window.

At Level A processing median value 70 is confirmed as the effective median X_{med}, since K1 < median < K2. Thereafter proceeding to Level B, the two impulses are detected and switched with the effective median as shown in Figure 5. Finally, at this level, the pixels are re-sorted and processing continues to the next level..

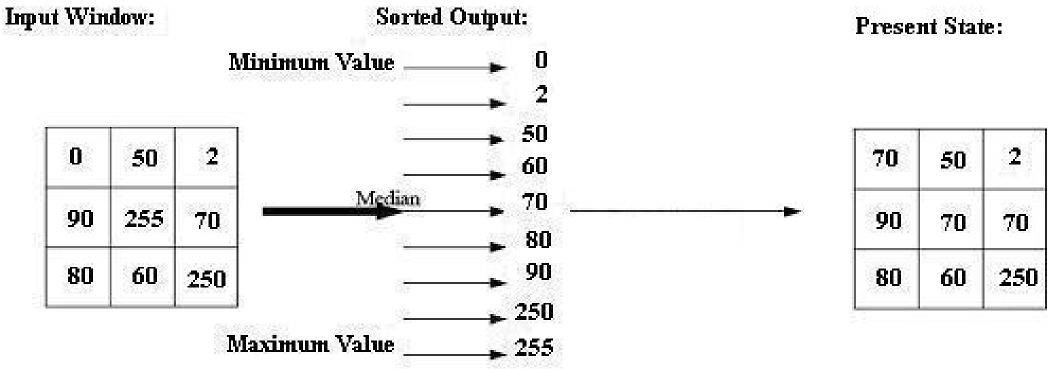


Figure 5: Impulses switched with the effective median.

At Level C, first D is computed by considering the sub-list starting from the second value and ending at the eighth value. D is found to be equal to 10. Since 50-2=48 is greater than D, the value 2 is switched with the effective median. Also, 250-90=160 is greater than D and so the value 250 is switched with the effective median. The output window in Figure 6 shows these replacements.

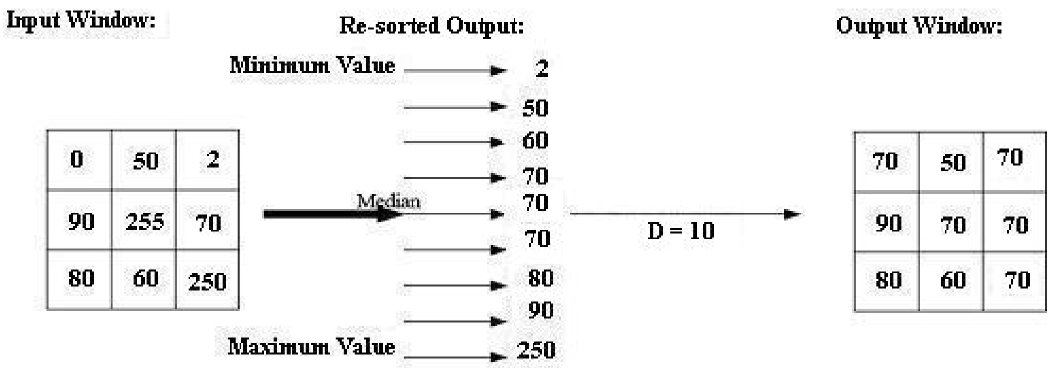


Figure 6: D is computed and used to detect distortions the extremes of the re-sorted list.

Experimental Results

In order to test the performance of the proposed algorithm, experiments were conducted on the cameraman image shown in Figure 7 with its grey level histogram. Intensive simulations on MATLAB 7.40(R2007a) platform were carried out on several versions of the image corrupted with Impulse noise (salt and pepper) and Gaussian noise. Figure 8 shows results achieved by the proposed algorithm in comparison of those achieved using the standard median filter and the adaptive median filter when the image is 50% corrupted.

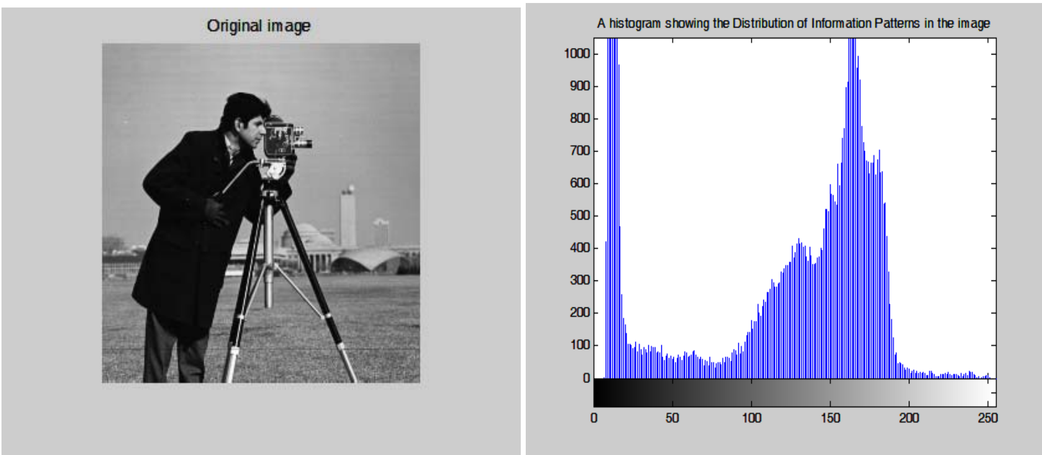
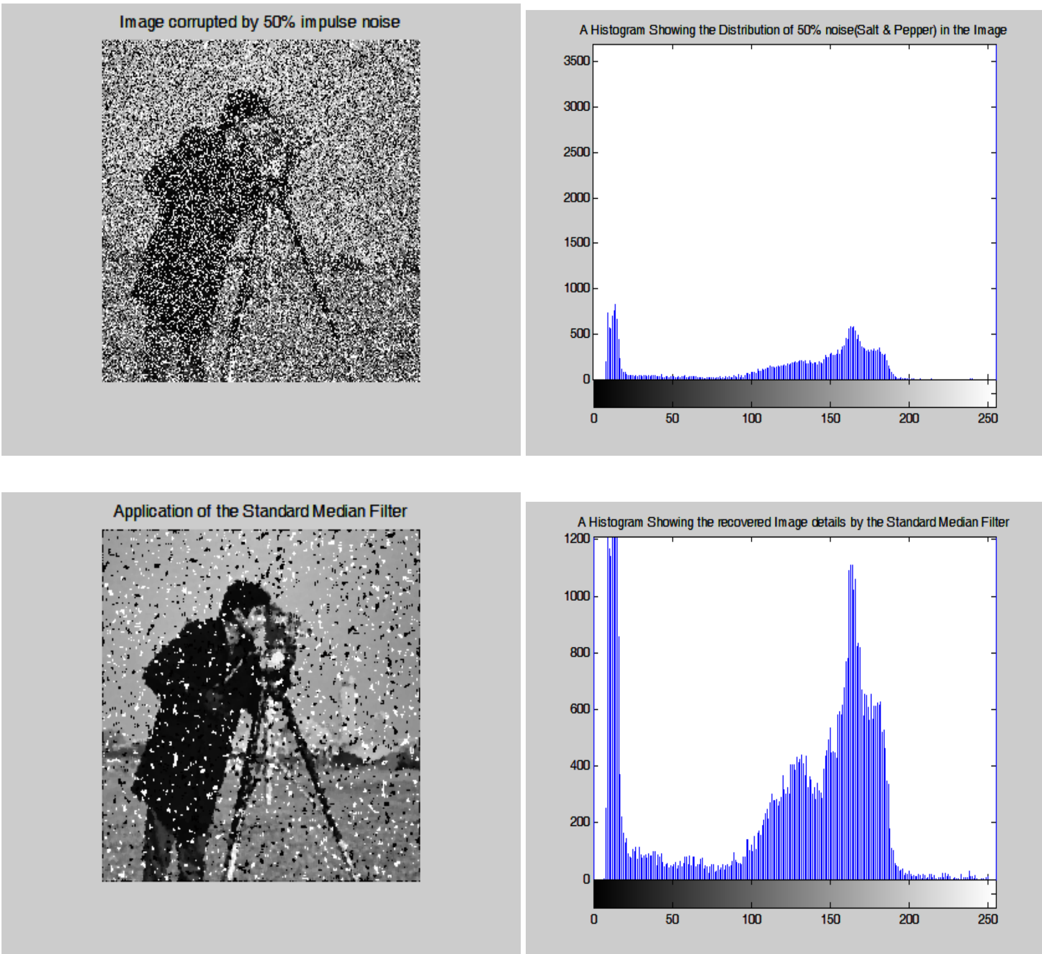


Figure 7: The cameraman image (a) and its grey level histogram (b).



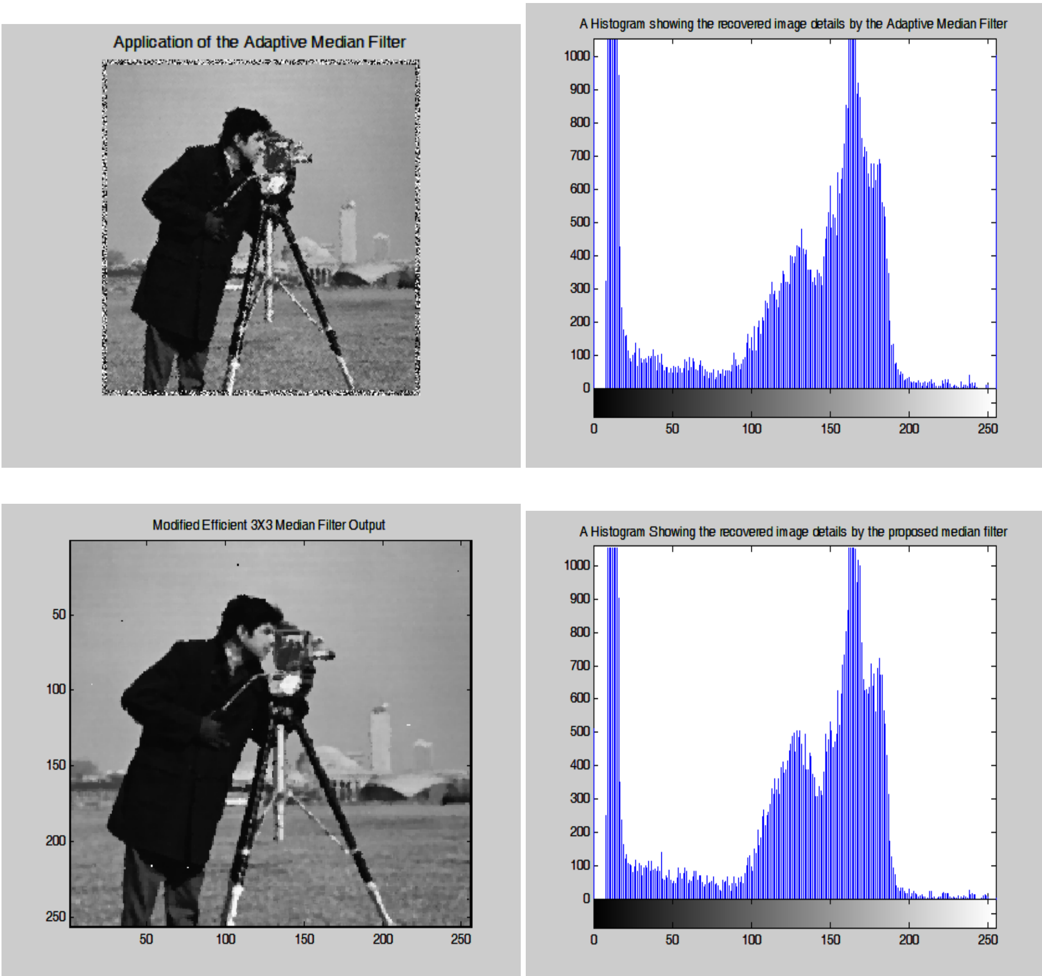


Figure 8: The cameraman corrupted by 50% impulse noise image (a), its grey level histogram (b); the image after standard median filtering (c), its grey level histogram (d); the image after adaptive median filtering (e), its grey level histogram (f); and the image after filtering using the proposed algorithm (g), its grey level histogram (h).

The peak signal-to-noise ratio is one of the best known techniques for assessing the amount of noise that an image is polluted with and, for that matter, the amount of noise left in a filtered image. The peak signal-to-noise criterion is adopted to measure the performance of various digital filtering techniques quantitatively. This is defined as

$$PSNR = 10 \log_{10}\left(\frac{255^2}{MSE}\right), \text{ where } MSE = \frac{1}{MN}\sum_{j=1}^{M}\sum_{i=1}^{N}\left(G(i,j) - F(i,j)\right)^2$$

M and N are the total number of pixels in the column and row of the image. G denotes the noisy image and F denotes the filtered image. The quantitative result in Table 1 and the graph in Figure 9 show that the proposed effective median filter performed best in terms of impulse noise removal in a corrupted image than the other filters.

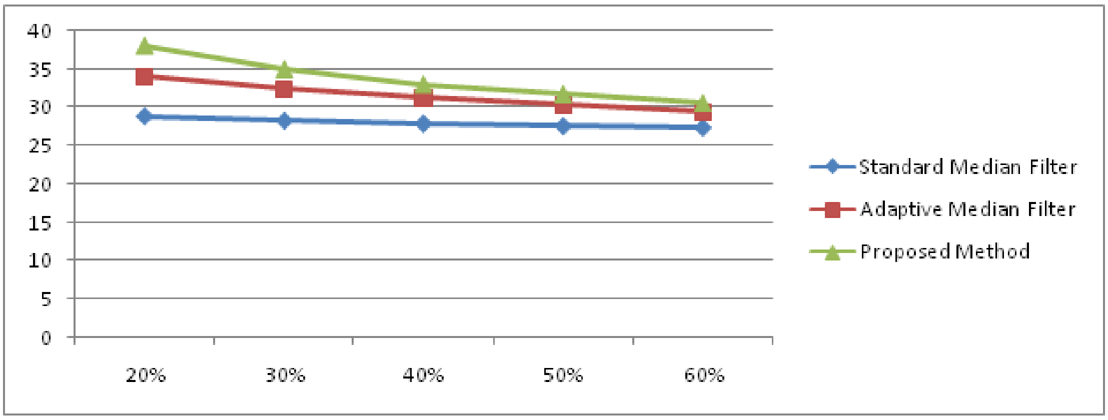


Figure 9: A Graphical representation of the result of the peak signal-to-noise ratio in the filtering techniques

Table 1: Peak signal-to-noise ratios.

Filter Methods	20% Impulse noise	30% Impulse Noise	40% Impulse noise	50% Impulse Noise	60% Impulse Noise
Standard Median Filter	28.8494dB	28.2734dB	27.9163dB	27.6012dB	27.3972dB
Adaptive Median Filter	33.9901dB	32.3710dB	31.287dB	30.3192dB	29.4614dB
Proposed Method	38.0638dB	35.0285dB	33.0720dB	31.8273dB	30.6626dB

Conclusion

Digital images are often corrupted by Impulse noise due to errors generated in noisy sensor, errors that occur in the process of converting signals from analog-to-digital and also errors that are generated in the communication channels. In order to remove impulse noise and enhance the affected image quality, we have studied the median filter and have developed a method based on an improved median filtering algorithm. The proposed method is a spatial domain approach and uses the overlapping window to filter the signal based on the selection of an *effective* median per window. Our *effective median filter* has been applied to images corrupted by impulse noise and relatively small amount of distortions (like Gaussian noise and small blurring components) in experimental simulations. Experimental results indicate that the proposed method performs significantly better in preserving image details and also preserving image edge information. The proposed method achieves better results when applied to images corrupted by impulse noise (salt and pepper) than in images corrupted by Gaussian noise. We repeated the experiments with the standard median filter and the adaptive median filter. Comparisons of results using the peak signal-to-noise ratios indicate that the proposed effective median filter achieves better results than either of the standard median filter and the adaptive median filter.

References

[1] Konstantinides, K., and Bhaskaram, V., 1996, “Monolithic architectures for image processing and compression,” IEEE Computer Graphicsand Application, pp.75-86.
[2] Wang, W., Swamy, M. N. S., and Ahmad, M. O., 2004, “RNS Application for Digital Image Processing,” 4th IEEE international workshop on System-on-chip for Real-time Application, pp. 77-80.
[3] Nodes, T. A., and Gallagher, N. C., 1982, “Median filters: Some modifications and their properties,” IEEE Trans. Acoust., Speech, Signal Processing. 30(5), pp. 739-7.
[4] Gonzalez, R.C., and Wood, R.E., 2007, Digital Image Processing, Prentice-Hall, India, Second Edition.
[5] Umbaugh, S. E., 1998, Computer Vision and Image Processing, Prentice-Hall, Englewood Cliffs, NJ, USA.
[6] Yli-Harja, O., Astola, J., and Neuvo, Y. , 1991, “Analysis of the properties of median and weighted median filters using threshold logic and stack filter representation,” IEEE Trans. Signal Processing, vol. 39, no. 2, pp. 395–410.
[7] Ko, S.-J., and Lee, Y. H., 1991, “Center weighted median filters and their applications to image enhancement,” IEEE Trans. Circuits and Systems, vol. 38, no. 9, pp. 984–993.
[8] Ghandeharian, B., Sadoghi, H., Homayouni, F., 2009, ” Modified Adaptive Center Eighted Median Filter for Uppressingimplusive noise in Images,” international journal of Research and Reviews in Applied Sciences, Vol. 1, Issue 3, pp. 219-227.
[9] Eng, H.-L., and Ma, K.-K., 2001, “Noise adaptive soft-switching median filter,” IEEE Trans. Image Process., vol. 10, no. 2, pp. 242–251.
[10] Pok, G., Liu, J.-C., and Nair, A. S., 2003, “Selective removal of impulse noise based on homogeneity level information,” IEEE Trans. Image Processing, vol. 12, no. 1, pp. 85–92.
[11] Dhanasekaran, D., Bagan, K., 2009, “High Speed Pipeline Architecture for Adaptive Median Filter,” European Journal of Scientific Research, Vol.29, No.4, PP.454-460.
[12] Chang-Yanab, C., Ji-Xiana, Z., Zheng-Juna, L., 2008, “Study on Methods of Noise Reduction in a Stripped Image, the International Archives of the

Photogrammetry," Remote Sensing and Spatial Information Sciences, Vol XXXVII. Part B6b, Beijing.

[13] Bezerra Candeias, A. L., Mura, J. C., et al., 1995, "Interferogram phase noise reduction using morphological and modified median filters,".

[14] Fisher B., Perkins S., Walker A., and Wolfart E., 2005, Hypermedia Image Processing Reference, University of Edinburgh, UK.

[15] Hussain, Z., Digital Image Processing–Practical Application of Parallel Processing Techniques, Ellis Hovwood, West sssex, UK, 1991.

Biographies

KWAME OSEI BOATENG is a senior lecturer in the Department of Computer Engineering at Kwame Nkrumah University of Science and Technology in Kumasi, Ghana, and heads the KVCIT of IDL of the same university. He earned a B.S. in Electrical/Electronic Engineering in 1991 from KNUST, an M.S. in Computer Science in 1997 from Ehime University, Japan, and a Doctoral degree (in Information Systems Engineering, 2000) from Ehime University, Japan. Dr. Boateng has worked as a researcher at Fujitsu Laboratories Ltd., Japan and was an ICT consultant for KNUST. His research interests include, design and test of logic circuits, reconfigurable instrumentation, residue number system applications and digital signal processing.

BENJAMIN WEYORI ASUBAM received the bachelors' degree in Mathematical Science (Computer Science Option) from the University for Development studies in 2006. He was been working in the Department of Computer Science at University for Development Studies since 2007 as a senior Research Assistant. He is currently a candidate of MPhil Degree program in Computer Engineering at Kwame Nkrumah University of Science and Technology. His present research interests are in the areas of image processing, digital signal processing, algorithms design, VLSI implementation for image processing and Residue Number System.

DAVID SANKA LAAR received the Bsc. in Computer Science from the University of Science and Technology, Kumasi Ghana in 2002. After working for two years as an Instructor at the Bolgatanga Polytechnic he furthered his education at The University of Manchester where he received the MSc in Management and Information Systems in 2005. He returned to the Bolgatanga Polytechnic and worked as a lecturer from 2006 to 2009. In 2009 he Joined the University for Development Studies where he currently lectures various courses in Computer Science at the Undergraduate level. His research interest includes, Information Systems Development in Developing Countries, Community Informatics, and E-commerce in Developing Countries.