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Analysis of Euclidean Denoising Algorithm for Medical Image Modalities

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Abstract: Medical images are often corrupted by impulse noises during the process of medical image acquisition and transmission. Hence, an efficient denoising technique is very important for the medical image processing applications before diagnosing. In this study, Euclidean detector noise filtering algorithm is proposed which detects and removes the impulse noise from the noise affected images, especially while compared with other state-of-the-art methods such as a switched median filter and selective median filter interms of medical image quality and mean square error. The process of impulse noise detection includes finding of the Euclidean direction, through the estimation of standard deviation in various directions of the filtering window. It also preserves the edges in the medical images during the denoising process. The main contribution of this study is to detect and reduce the impulse noises from the medical images for further medical diagnosis. The proposed method has been tested using different modalities of 20 medical images and proved to provide a better visual quality when compared to conventional methods.

Key words: Euclidean direction, image quality, image modality, impulse noise reduction, medical images

INTRODUCTION

Impulse noise is a major factor affecting the contents of a digital image. Impulse noise occurs due to several reasons such as synchronization errors in digital recording, electromagnetic interference, abrasions in recording disks and problems with in communication devices (Trahanias and Venetsanopoulos, 1993). Impulse noise deforms the image pixels while replacing the original pixel values by fixed values or random values. Salt and pepper noise can be considered as an example for fixed-value impulse noise, in which the gray value is a fixed value, i.e., either 0 or 255. But, in random-value impulse noise, gray value is a value between (0255) since, the noise is distributed evenly. It can be understood that both the original pixel and the random valued impulse noise has the same range of values. Therefore, random valued impulse noise requires more effort to be removed.

The general amplifier noise model (Wang and Zhang, 1999) is additive, Gaussian and independent of the signal intensity. This noise is caused mainly due to thermal noise, also which includes there set noise from capacitors, called as noise. In color cameras, there may be more noise in the blue channel due to more amplification at the blue color channel thanthe r in ed or green channel. Amplifier noises are most part of the 'read noise' (i.e., constant noise levels in dark are as of the image) in an image sensor.

Image processing often requires some specific methods for noise reduction on an image. The median filter is anon-linear digital filter which is most popularly used to remove impulse noises. Even though, median filter reduces some of the image details, it preserves the edges by uniform modification of the noise affected pixels and the noise-free pixels. Other popular algorithms are present which eliminates impulse noises present and maintains only the fine details of the image but, the detection process of these algorithms leads to losing of certain image details. Hence, all these techniques preserve the original pixels intact and detect and restore only the noisy pixels. The performances of conventional filters are good only with images affected with low noise densities and is very poor when the noise ratio reaches above 40%. Recent statistic filter finds the relative difference to detect more edge pixels, by implementation of statistic of rank-ordered absolute difference over the relative difference image and not over the noise corrupted image.

As an advanced method compared with standard median filtering our algorithm performs spatial processing to preserve detail and smooth non-impulsive noise. A major advantage to this adaptive approach to median filtering is that repeated applications of this Adaptive median filter preserves way edges or other small structure in the image. The method is particularly effective for the images with very high noise ratio.

The Centre Weighted Median (CWM) filter which is a weighted median filter which is giving more weight to

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the centre value of each window. This filter can preserve image details by suppressing additive white Gaussian noise or impulse type noise. This filter gives more weight to the central value of a window and thus, it is easier to design and implement than the weighted median filters.

Chen *et al*. (1999) proposed a Tristate Median (TSM) filter which preserves the image details while effectively suppresses the impulse noise. They incorporated both Standard Median (SM) filter and the Centre Weighted Median (CWM) filter to forma noise detection frame work which determines whether a pixel is corrupted or not, before applying filtering unconditionally. The performance results showed that the proposed filter considerably performs much better than other median filters by balancing the trade-off between noise reduction and details preservation. Chen and Wu (2001a) proposed a median-based impulse detection strategies tend to work well for fixed-valued impulses but poorly for random-valued impulse noise. Their method forms estimates based on the differences between the current pixel and the outputs of Centre-Weighted Median (CWM) filters with varied centre weights. The experiments showed that their scheme consistently worked well in suppressing both types of impulses with different noise ratios. Chen and Wu (2001b) proposed a general framework of median based switching schemes, named as Multi-State Median (MSM) filter. By using simple thresholding logic, the output of the MSM filter is adaptively switched among a group of Centre Weighted Median (CWM) filters having different centre weights. As a result, the MSM filter was proved to be equivalent to an adaptive CWM filter with a space varying centre weight dependent on local signal statistics. Several simulations were performed to evaluate the efficiency of the proposed filter. Chan *et al*. (2004) proposed two-stage iterative method for removing random valued impulse noise. In the first stage, an adaptive centre-weighted median filter is used for identifying pixels which are likely to be corrupted by noise. In these condstage, these noise candidates are restored using a detail-preserving regularization method which allows edges and noise-free pixels to be preserved. These two phases are applied alternatively. Simulation results proved their method to be considerably better than other methods using only non-linear filters or regularization. Yu *et al*. (2008) proposed edge preserve based impulse noise detection and removing algorithm. This method highly concentrated on pixels in edge regions only and did not concentrate on the pixels in other regions. Estrada *et al*. (2009) used stochastic image denoising model for detection of impulse noises. This Stochastic modeling produced complex design methodologies and mathematical formulation.

Rawat and Singh (2014) have proposed trimmed global mean filtering technique to remove the impulse noises from the images. This method is used to remove various types of degradation like stripes, scratches, blotches and streaks. The algorithm uses [3×3] selective window ensuring fast algorithm. It provided 30 dB PSNR for standard images. Jansiraini (Rabbani *et al*., 2009) have proposed an efficient filtering median filter based technique which is used to remove the impulses so that the noise free image is fully recovered with minimum signal distortion. The best and most widely used non-linear digital filters are median filters. The performance of the algorithm has been tested at low, medium and high noise densities on gray-scale images .It provided maximum of 44.4 db for PSNR. Priya and Pugazhenthi (2014) have proposed a new decision based morpho filtering technique for salt and pepper noise corrupted in the digital color images. This technique is evaluated by bench mark images such as Lena, Barbara and Peppers. It provided edge preservation while image restoration. Wang *et al*. (2015) have proposed low-rank prior technique to detect and remove the impulse noises from the images. This single-patch method gave generalized joint low-rank and sparse matrix recovery framework to simultaneously detect and remove non-point wise random-valued impulse noise. Verma *et al*. (2015) have improved adaptive median filter to detect and remove the impulse noises and the edges were preserved.

The conventional methods have used pixel wise approach for the detection and reduction of impulse noises from the images. These methods did not consider the edge preservation during image restoration, thus reduces the PSNR. The proposed methodology described in this study used region-wise approach for the detection and reduction of impulse noises from the images. The proposed method will significantlt reduces the denoising latency and improves the image quality.

MATERIALS AND METHODS

The proposed medical image algorithm includes two steps; dividing the filtering window into eight equal directions and finding of the euclidean direction. The Euclidean direction is the direction with more identical pixels. The main contribution of this research is to detect the pixel as noisy or not by using euclidean direction. The proposed algorithm is explained as:

Step 1: The medical image which is to be denoised is first split into m×n pixel blocks as shown in Fig. 1. These blocks should not be over lapped with other. In this research, we split the noisy image of size 9×9 sub blocks.

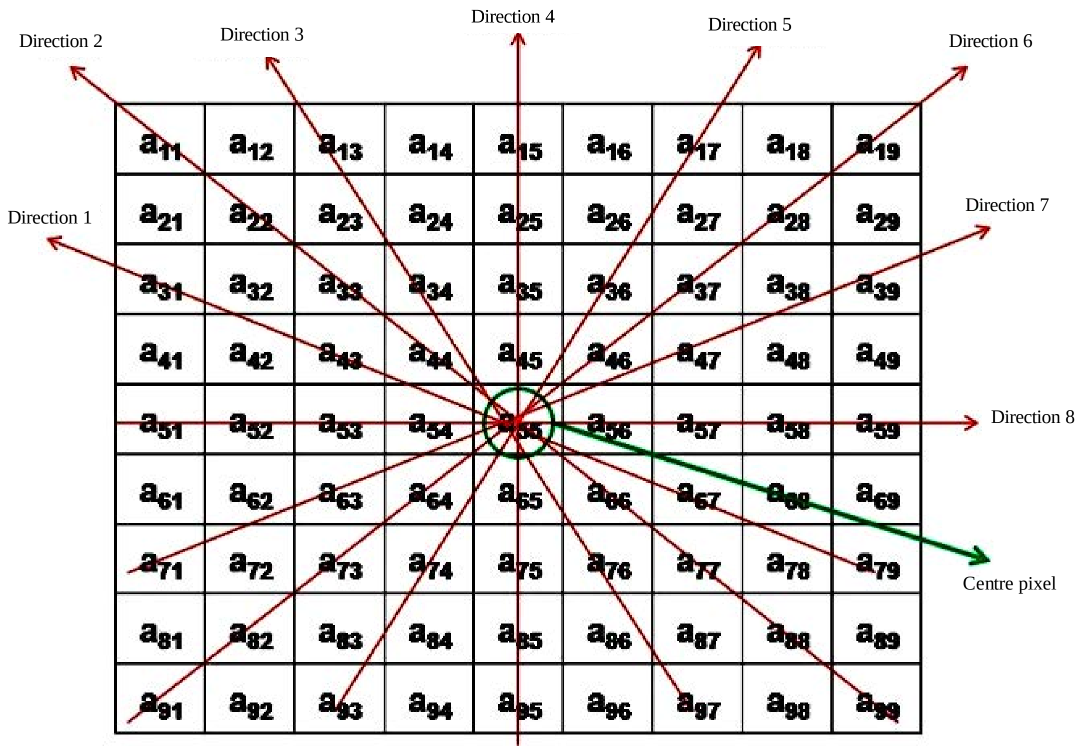

Fig. 1: The 9×9 windows plitin to 8 directions, each direction is noted as Direction 1-8 and center pixel is considered for noise inspection

Step 2: Initially first sub-block (of size 9×9) is divided into eight orthogonal direction patterns such as 30 degrees each and each orthogonal directional pattern consists of 9 pixels.

Step 3: Remove the current pixel from the selected orthogonal direction pattern and hence it gives eight pixels in each eight directions.

Step 4: The orthogonal direction patterns are sorted in ascending order and then from these sorted values, remove the lowest and highest vector patterns.

This sorted vector contains both minimum and maximum value pixels. Similarly, all corresponding minimum and maximum value in each orthogonal vector patterns are determined and their minimum and maximum values are noted.

Step 5: Find the Standard Deviation (SD) for eight orthogonal sorted direction patterns:

$$SD_{n=}\mathrm{Sqrt}\left[\sum\left(x-x_n\,2/N\right)\right]$$

where, 'N' represents the number of pixels in each direction and n varies from 1-8. The X_n is the piexls in a each direction and x is the center pixel.

Step 6: Find the minimum of these standard deviations and the corresponding direction is considered as the Euclidean direction (dir_{opt}):

$$dir_{opt}=\min\left(SD_1,SD_2,SD_3,SD_4,SD_5,SD_6,SD_7,SD_8\right) \quad (1)$$

Step 7: Determine the similarity factor 'S' between the current pixel (xct) under process and the pixels in the optimum direction. The value of 'S' can expressed by:

$$S=\sum abc\left(\frac{Diropt-xct}{255}\right) \quad (2)$$

Step 8: Set the threshold T and verify whether the current pixel under process is either noisy x_{noisy} or an original pixel x_{orig}:

$$X_{out}=\begin{cases}X_{orig};\text{if}\in T,\{0\le T\le k-3\}\\ X_{noisy};\text{else}\end{cases} \quad (3)$$

The noisy pixel is immediately omitted after detection and it is not carried over in further steps and ‘k’ represents the denoising window size. Here, ‘k’ is considered as 9.

Step 9: Apply density weighted filter over the pixels which were detected as noisy pixels and its surrounding pixels.

Step 10: Determine Euclidean weight 1 and 2 of the noisy pixelas:

$$\text{Ed1} = \sum \text{Xi} \tag{4}$$

where, ‘i’ represents the neighboring pixels of noisy pixel to be denoised:

$$\text{Euclidean weight2} = \text{Ed2} = \frac{1}{n} \sum (\text{xi} - \text{Ed1}) \tag{5}$$

where, ‘n’ represents the histogram count of the noisy pixel to be denoised.

Step 11: Compute density weight function as:

$$\text{Fcdf} = e\left[\frac{(\text{xi}-\text{Ed1})^2}{\text{Ed2}}\right] \tag{6}$$

Step 12: Denoised Pixel is finally computed as the summation of product of density weight function of the surrounding neighbor pixels and it is represented as;

$$\text{Denoised pixel} = \sum \text{Fcdf} \times \text{xi} \tag{7}$$

All the above steps are processed as a flow and are clearly explained briefly as a pseudo code in Algorithm A.

Algorithm A; Pseudo code for proposed denoising methodology:

Input: Noise image. Output: Denoised image.
Upon receiving noisy image
Divide the image in to m×n sub blocks then
Divide the sub block into eight orthogonal directions by considering 30 degree each orthogonal direction.
Remove the current pixel from the selected orthogonal direction pattern
Sort the ODP (optimum direction pixels) in ascending order
Remove the lowest and highest vector patterns
Find the standard deviation //the minimum standard deviation gives the optimum direction
End
Find Similarity factor then
Set threshold//threshold must be close to zero
End
If current pixel is below to threshold then
Pixel is noise-free else
Pixel is noisy
Apply density weight function over detected noisy pixels
End
End

RESULTS AND DISCUSSION

The number of medical images from various open access dataset is utilized in this paper to show the performance of the proposed noise reduction technique in efficient manner. The 20 brain images are used in this paper which are accessed from publicly available open access database. The 20 mammogram images are used in this paper which are accessed from publicly available open access database and 20 CT liver images are used in this paper which are accessed from publicly available open access database.

The principle aspects interms of edge preserving concept for high density impulse noise are tested in MATLAB environment and its results are evaluated with the conventional noise removal algorithms. To verify the characteristics and the quality of denoised medical images of the modified denoising algorithm, a variety of simulations are carried out on the different medical image modalities: brain MRI image, liver and mammogram images. The image is tested with various high level noise densities 40, 50 and 55% in this research.

Then, the proposed algorithm is employed to detect impulse noise and restore the corrupted image. Figure 2-4 show the simulation results achieved through MATLAB. The metrics for comparison are defined using the parameters PSNR (Peak ssignal to noise ratio) and MSE (Mean square error):

$$\text{PSNR} = 20\log_{10}\frac{225^2}{\sqrt{\text{MSE}}} \tag{11}$$

$$\text{MSE} = \frac{1}{m \times n}\sum_{0}^{m-1}\sum_{0}^{n-1}\left\|f(i,j) - g(i,j)\right\|^2 \tag{12}$$

Where:

m = Represents width of the image
n = Represents height of the image
f(i, j) = Represents each pixel in the source image
g(i, j) = Represents corresponding piexl in noise reduced image (1.16)

The image is tested with various high level noise densities 40, 50 and 55% in this research. The proposed denoising algorithm is tested on large number of test medical images and its performance is compared with other conventional techniques in terms of PSNR and MSE. The 20 brain images are used in this study which is accessed from publicly available open access database. The 20 mammogram images are used in this study which is accessed from publicly available open access database and 20 CT liver images are used in this study which are accessed from publicly available open access database.

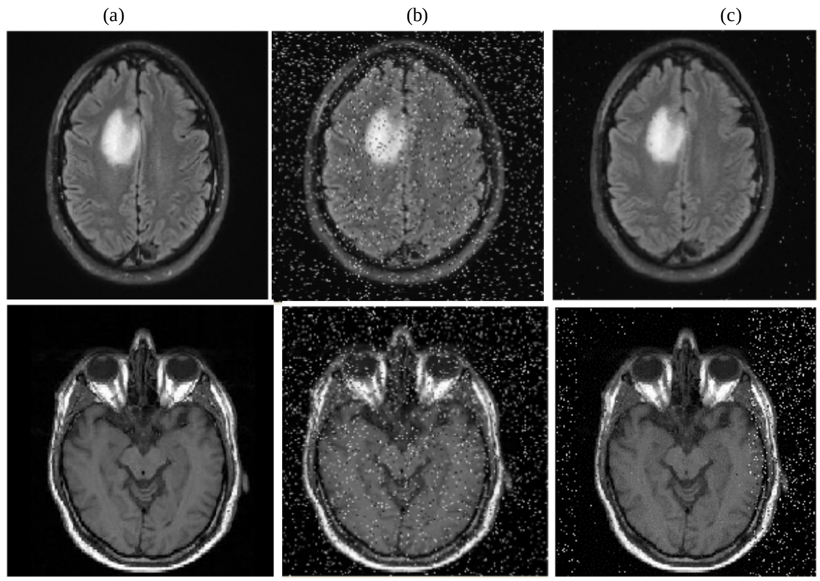

Fig. 2: Denoising of brain images: a) Source brain image; b) Brain images affected by impulse noise; c) Noise reduced images of proposed approach

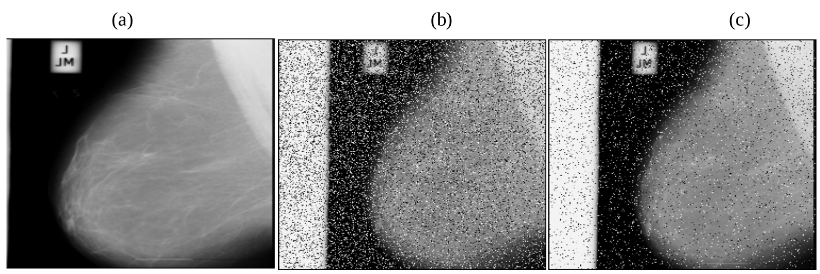

Fig. 3: Denoising of mammogram images: a) Source mammogram image; b) Mammogram images affected by impulse noise; c) Noise reduced images of proposed approach

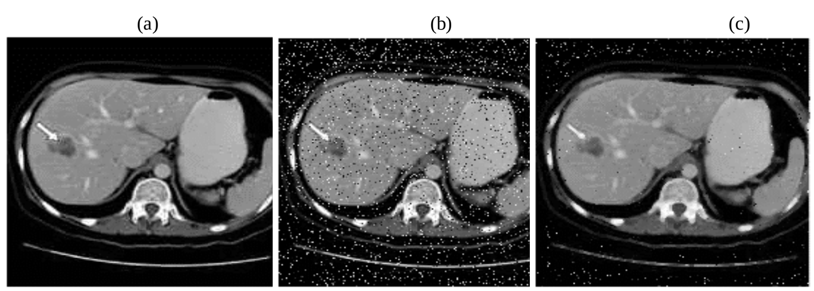

Fig. 4: Denoising of liver images: a) Source liver image; b) Liver images affected by impulse noise; c) Noise reduced images of proposed approach

Table 1 and 2 compare the performances of the proposed method with other existing denoising methods interms of PSNR and MSE, respectively. Both the results prove that the proposed method gives considerable results at low noise levels but it attains a superior performance than, the other methods at high noise ratios. This is mainly due to the accurate selection of the optimal direction which suppresses the pixels that are different to the pixels present in the optimal direction and vice-versa. The second iteration is applied on the first restored image in oreder to improve the accuracy. The experimental results show that the fine details and thin lines are preserved by propose method.

Table 1: Performance comparison of proposed method interms of PSNR

	Noise density (%)				
Methodology	10	20	30	40	50
Proposed methodology	44.45	42.18	41.98	39.10	37.19
Progressive switching median filter (Wang and Zhang, 1999)	22.68	21.77	20.95	20.16	19.14
EPRIN (Yu *et al*., 2008)	21.47	21.36	21.31	20.76	20.14

Table 2: Performance comparison of proposed method in terms of MSE

	Noise density (%)				
Methodology	10	20	30	40	50
Proposed methodology	15.18	16.10	23.98	29.18	29.27
Progressive switching median filter	17.25	26.12	28.19	29.12	29.67
EPRIN	18.29	19.87	27.98	29.87	29.95

Table 3: Quality level estimation of medical images

Image sequence	PSNR	MSE
1	44.14	29.16
2	42.18	26.11
3	41.11	18.28
4	43.27	17.65
5	46.18	18.76
6	47.12	19.24
7	45.17	18.98
8	43.12	22.01
9	36.80	18.95

Table 4: Performance comparison interms of PSNR (dB)

	Noise density methodology (%)								
Methodology	10	20	30	40	50	60	70	80	90
Proposed methodology	44.45	42.18	41.98	39.10	37.19	36.12	34.19	31.90	28.98
Trimmed global mean filtering technique (Rawat and Singh, 2014)	30.00	28.17	26.90	24.19	22.10	21.09	20.07	19.07	18.12
Modified median filter (Rani and Kowsalya, 2014)	44.40	40.08	38.16	36.89	34.19	32.17	30.12	29.01	27.08
Progressive switching median filter (Wang and Zhang, 1999)	22.68	21.77	20.95	20.16	19.14	18.01	17.19	14.10	13.18
EPRIN (Yu *et al*., 2008)	21.47	21.36	21.31	20.76	20.14	19.98	17.28	16.96	15.01
Adaptive median filter (Verma *et al*., 2015)	32.10	30.08	28.19	26.05	22.67	18.01	17.16	15.36	15.27

Table 5: Performance comparison of proposed method interms of denoising latency

Methodology	Elapsed denoising latency (s)
Proposed methodology	12
Progressive Switching median filter (PSW)	15
EPRIN	16

The PSNR and MSE values obtained for a set of images at a noise density of 10% are tabulated and clearly shown in Table 3. The performance of the proposed denoising technique is compared with other denoising methods interms of the denoising latency as tabulated in Table 4.

The proposed method achieves 28.98 db PSNR even when the noise density is 90%. The PSNR comparisons at various noise densities with conventional methods are stated in Table 4. Latency is a performance evaluation parameter for denoising the images. It is defined as the time taken for denoising the given image. This is very important for real time denoising environment such as live programs and telemedicine methods. The system is considered as good if it supports low latency. Our proposed methodology provides ~12 sec for denoising the medical image. Table 5 shows the comparison of our proposed with the conventional techniques in terms of denoising latency.

CONCLUSION

The medical images are frequently affected by impulse noises while capturing the images. The main contribution of this study is to detect and remove the impulse noises from the images. In this study, Euclidean detector noise filtering algorithm is proposed and it works superior than the conventional filters such as a switched median filter and selective median filter interms of medical image quality and mean square error. The proposed method has been tested using different modalities of medical images and proved to provide a better visual quality when compared to other conventional methods. The performance of the proposed methodology is analyzed interms of PSNR and latency.

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