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Implementation and Comparison of the Spatial Denoising Filter for Impulse Noise on MIAS Dataset

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Abstract— Image preprocessing is the important phase in digital image processing domain to analyze the undesirable signal present in an image and removal of the same. For any further processing of an image, noise removal is mandatory to get the desired resultant. Before applying any noise removal algorithm to an image, it is obligatory to understand what kind of noise that exactly presents in an image. In this paper, we have handled the impulse noise presence in mammogram image and various spatial based median filters are applied to it. Initially, to confirm the impulse noise presence, the sub-window of an image is subjected to undergo the detection process, where the impulse noise pixels are identified. Secondly, for the detected noise window the traditional median filter is applied. This process does not affect the image quality and produces the noise-free enhanced image. Finally, we have experimented and compared the five different median based denoising algorithms, each one has different detection framework and found the best denoising algorithm for impulse noise removal with the help of qualitative and quantitative metrics.

Keywords— Preprocessing, Impulse Noise, Denoising, Mammogram Image.

I. INTRODUCTION

In a recent scenario, women are facing breast cancer which is a major concern which may sometimes even leads to death. The early detection of the malignant tissue in breast will lessen the possibility of severe disease. A mammography is a type of radiography where it uses different levels of processes to capture and produces the breast images for diagnosing the structure of the cancer cell. Even though there exist several techniques like ultrasonography and Magnetic Resonance Imaging, the physician commonly prefers the mammography for examining the breast cancer because of a low dosage of radiations. There are some common characteristics of breast cancer to be identified such as microcalcifications, architectural distortions, masses and bilateral asymmetry. Among these characteristics, microcalcification is considered to be the toughest part of the prediction of cancer. The remaining is not taken into consideration because of its texture and size properties which are well defined as cancer. Generally, mammogram images contain the noises from various sources. If microcalcification affected breast image is degraded with noise pixel element it is very difficult to predict the true positive result than another characteristic of breast cancer.

The procedure of mammography as similar to x-rays, however, it uses the low doses which give the very low-resolution images with noises in it. The breast organ consists of sensitive soft tissues, so high ionizing radiation usually avoided.

Medical imaging tools play an almost important in medical practice and an invaluable mean for establishing a diagnosis. The use of computers for medical image analysis offers abroad range of new capabilities (Campilho, 2000) [1]. The preprocessing is an important step in medical images which should be carefully done due to poor captured image quality (Ramani et al. 2013) [2]. Tashk et al. (2013) developed the system for analysis of histopathological image for grading the breast cancer [3]. Even though many existing system detects the malignant tissue even though there exist the chances for miss-detecting the extra tissue which is also considered as malignant due the presence of noise in it (Halalli and Makandar, 2018) [4]. Buades et al. (2005) proposed a new measure to evaluate and compare the de-noising method namely loan cal smoothing filters [5]. Alajlan (2010) introduced the two-step noise reduction process such as detection and estimation. This algorithm maximizes the contribution of noise-free neighbours in detecting and correcting the noisy pixels. This methodology does not need the classical recursive implementation which performs sequential row by row scanning [6]. For the noise filtering process non-local means based on non-local averaging of all pixels in an image. Garnett et al. (2005) introduced the local image statistic for identifying noise pixels in images corrupted with impulse noise of random values. The statistical values quantify how different in intensity the particular pixels are from their most similar neighbours. This work removes the additive Gaussian noise and impulsive noise efficiently [7]. Piao et al., (2018) applied the bilateral filter only in the high gradient region of the image incorporated with the Gaussian filter [8].

The conventional denoising techniques can suppress the noises effectively, but it fails to maintain the quality of an image and makes the image blur. Sun and Neuvo (1994) proposed the switching scheme for median filtering [9]. Nasri et al. (2013) developed the Switching Non-Local Mean (SNLM) filter for the high-density salt and pepper noise reduction. In the first phases, impulse noise is detected based on the extreme grey-level of an image [10]. Mingliang et al. (2016) demonstrated the classical NLM algorithm for eliminating the noise from the medical images by using the noise weighting function and parallelizing concept [11]. Singh et al. (2017) used the homomorphic scheme with anisotropic diffusion filter in db2-type wavelet transform. Linear and non-linear used here to approximate the blurring effect of the SAR image dataset [12]. Wang et al. (2018) are with the denoising algorithms uses the singular value difference between the noisy and original image which will vary along with the noisy intensity [13]. Nair and Mol (2013) investigated the efficient direction based Adaptive Weighted Switching Median (AWSM) filter for restoring the corrupted image from impulse noise [14]. Gupta et al. (2015) presented the concept of the adaptive dual threshold for the detection of random-valued impulse noise along with a simple median filter at noise removal stage [15]. Faragallah et al. (2016) developed the Adaptive Switching Weighted Median (ASWM) filter framework. This filter has the detection and removal stage. In the first step, it classifies the noise and non-free pixel into two categories by checking noise candidate with the local mean value. In the second phase noisy pixel is replaced by weighted median values using an adaptive weighted median filter [16]. Meher and Singhawat (2014) justified the improved Recursive Adaptive Median Filter (RAMF) for restoring the corrupted images from high-density impulse noise. The Adaptive operation of the filter is justified with the variation in the size of the working window which is centred at noisy pixels. Based on the presence of noise-free pixel, the size of working window changes. The corrupted pixels are removed by the values using both noise-free pixels of the current working window and previously processed noisy pixels of that window. This combination provides the improved performance of the filter [17]. Ismaeil et al. (2017) developed a filter which has two-phases such as detecting and filtering using the algorithm which is based on decision rule [18].

Bakwad et al. (2009) proposed the approach to enhance the PSNR of the highly corrupted image affected by impulse noise. They have used the adaptive median filter and the BFO technique to denoise the highly corrupted image [19].

In this paper, the comparative study is made with four different spatial based denoising filters such as Directional Weighted Median Filter (DWMF), Modified Decision Based Unsymmetric Trimmed Median Filter (MDBUTMF), Recursive and Adaptive Median Filter (RAMF) and Adaptive Dual Threshold Median Filter (ADTMF). The implementation work is done with these filters to analyse each of its performance over impulse noise corrupted mammogram image. The mammogram image is taken from the MIAS dataset which contains benign, malignancy, normal type and this dataset is socially available one. The qualitative measures such as Peak-Signal Noise Ratio (PSNR), Mean Square Error (MSE) and Structural Similarity Index Measure (SSIM) are evaluated for these four different filters to find the efficiency.

This paper is organized as follows: Section 2 briefly describes the mathematical notation of the impulse noise model, Section 3 explains the materials used for this paper such as four median based denoising filters. In Section 4, implemented result and its performance are discussed elaborately. Finally, Section 5 concludes this paper.

II. IMPULSE NOISE MODEL

The impulse has the sparse light and dark distribution of pixel in an image which varies in colour and intensity from the background and also from the surrounding pixel. The value of the noisy pixel bears no relationship to the colour and surroundings. Generally, this noise will affect the small number of intensity based on their population density value.

The source of this noise includes the due to the physical interference, a speckle of dust inside the camera and also from the imaging sensor. The impulse noise model is formulated in Equation 1.

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

Where $b>$ *an* intensity b will appear as a light dot in the image. If $b<a$, then the intensity of b will appear as a dark black dot. If P_a or P_b is zero, then an impulse noise is called unipolar.

In addition, the impulse noise model is also called fat-tail distributed or salt & pepper noise or spike noise. The image which is corrupted by the impulse noise will have a dark pixel in the brighter background region and bright noise pixel in the darker background region. At the low density of its noise population it can easily find out and can be removed, but when the noise intensity increases, it is very difficult to find and remove the impulse noise from an image. If its density is less, it can easily eliminate by using dark frame subtraction, median filtering and interpolating around dark/bright pixels.

III. MATERIALS AND METHODS

The traditional median filter is the backbone for the spatially transform denoising filter. Instead of operating the median technique directly to a corrupted image, initially, it should be analyzed what kind of noise is occurred on that image. For removing the impulse noise from an image, a median filter is considered as the best one. But if the noise density is high, median filter fails to preserve the significant features in an image. In that scenario, the spatial filters should undergo two stage of the process such as detection of noise pixel and the removal of the same. For the detection scheme, many different techniques are handled so far to identify the corrupted pixel from the window. For modifying the detected pixel, the traditional median filter is applied to it. There exist various two-stage denoising filters each has different detection mechanism. Here some of the filters such as DWMF, MDBUTMF, RAMF and ADTMF are implemented for the impulse noise corrupted mammogram image and it is briefly discussed below.

i. Directional Weighted Median Filter

The impulse detector differentiates the current pixel with its neighbourhood pixel with four different directions. After the detection of the impulse noise pixel, it is not simply replaced with the median value but derives the information from four directions and replaces the candidates which are noisy [20].

$$x(i,j) = \alpha(i,j).y(i,j) + [M(i,j) - \alpha(i,j).M(i,j)] \quad (2)$$

Where, $\alpha(i,j)$ threshold value computation parameters in four different directions, $y(i,j)$ is the noise candidate pixel, $M(i,j)$ is the median value. In DWM, achieving the fine edge is easier but, it has the serious issue with the blurriness of the image, which subsequently reduces the quality of the image.

ii. Modified Decision Based Unsymmetric Trimmed Median Filter

The restoration of grey and colour image from high impulse noise is a difficult process. The Modified Decision-Based Unsymmetric Trimmed Median Filter (MDBUTMF) found the centre pixel to be noisy and it uses the median value of the selected window to replace it. In the selected window other than the centre pixel, the adjacent pixel value is found to be 0's and 255's and then it should be replaced by the mean value [21]. The algorithm step is given below:

Step 1: Select the 3×3 window. In the 3×3 window, $C_{i,j}$ represents the centre pixel.

Step 2: If 255< $C_{i,j}$<0, then it means the centre pixel is a noise free pixel. Keep that value unchanged.

Step 3: If $C_{i,j}$=0 and $C_{i,j}$=255, then it is found that the centre pixel is a noisy pixel.

Step 4: All the pixel around the centre pixel is surrounded by 0's and 255's, take the mean for the selected window and $C_{i,j}$ is replaced with the mean value.

Step 5: If the centre pixel alone contains 0's and 255's, it uses the median value to replace the $C_{i,j}$.

The MDBUTMF avoids the replacement of neighbouring pixel which is not noisy.

iii. Recursive and Adaptive Median Filter

The median-based noise reduction approach named Recursive and Adaptive Median Filter (RAMF) has detection and reduction phases. The corrupted pixel is filtered through the replacement process. The particular pixel alone is removed and it is done by non-noisy pixel or previously processed noisy pixel. This process is done recursively.

Initially, histogram analysis is made to separate the corrupted and uncorrupted pixel which is determined by two extreme noise peak obtained from the histogram. The values of the pixel from these two extreme is categorized into noise pixel. The value obtained between the two extreme is classified as a non-noisy pixel [22]. The algorithm steps are given below:

Step 1: Determine the 3×3 from the input image which is corrupted by impulse noise.

Step 2: If 3×3 window contains pixel value between the two extremes from the histogram peak, then centre pixel $C_{i,j}$ it is found to be noise-free pixel and it should be left unchanged.

Step 3: If the selected window contains one or more noise free pixel (obtained by histogram analysis), then replace the centre pixel $C_{i,j}$ with the median value.

Step 4: If the entire pixel in the 3×3 window is noisy, maximize the size of the window from 3×3 to 5 × 5 windows and check with the two sub-cases:

Case 1: If 5×5 window contains the one or more noisy pixel, then replace $C_{i,j}$ with the median value.

Case 2: If 5×5 window, entire pixel are noisy, then replace centre pixel ($C_{i,j}$) by the median value of already processed four adjacent neighbour pixel in the 3×3 window.

iv. Adaptive Dual Threshold Median Filter

The detection of Random Valued Impulse Noise (RVIN) and filtration with the standard median filter are done efficiently with the Adaptive Dual Threshold Median Filter (ADTMF) by Gupta et al. (2014). They have worked with the two threshold value for the detection of RVIN [15]. The averaging process is done for estimating the threshold value for the detection process and the standard median filter is used for the removal process. The detailed algorithm steps are given below:

Step 1: Partitioned the corrupted input image as 3×3 size.
Step 2: Dual threshold calculation is done using the averaging process on the selected window size. By the averaging process minimum and maximum threshold is determined.
Step 3: If a noisy candidate is detected, median value computation is done for the respectively selected window. Otherwise, move to the next window and continue with step 2.
Step 4: Replace the centre pixel ($Cp_{(i,j)}$) with the median value.
Step 5: Denoised image is produced.

IV. PERFORMANCE ANALYSIS AND DISCUSSION

The performance of the median based denoising filter is evaluated with qualitative factors like SSIM, PSNR and MSE. The visual results obtained from DWMF, MDBUTMF, RAMF and ADTMF techniques are shown in Figure 1.

Table 1: Performance comparison of median based spatial filters (Measure: PSNR)

Noise Density (%)	Corrupted Image	DWMF	MDBUTMF	RAMF	ADTMF
10	10.524	27.120	30.126	35.641	36.574
25	8.140	26.004	28.135	34.972	35.968
50	5.107	23.578	24.564	29.181	29.099
75	3.470	21.889	22.246	27.484	28.892
90	1.947	19.924	18.277	23.621	26.940

Table 2: Performance comparison of median based spatial filters (Measure: MSE)

Noise Density (%)	Corrupted Image	DWMF	MDBUTMF	RAMF	ADTMF
10	1.624	0.893	0.756	0.412	0.472
25	2.147	1.067	0.965	0.729	0.664
50	4.240	1.193	1.001	1.067	0.979
75	6.015	1.392	1.174	1.210	1.189
90	10.167	2.017	1.970	1.509	1.369

Table 3: Performance comparison of median based spatial filters (Measure: SSIM)

Noise Density (%)	Corrupted Image	DWMF	MDBUTMF	RAMF	ADTMF
10	0.203	0.596	0.542	0.668	0.714
25	0.107	0.513	0.501	0.603	0.620
50	0.094	0.466	0.464	0.462	0.512
75	0.054	0.307	0.372	0.366	0.401
90	0.013	0.267	0.244	0.307	0.367

From Table 1, it is clearly inferred that the ADTMF noise removal technique yields a superiority of the result when compared to the other three filters. The comparison result is also made with the corrupted image to analyze the performance of the noise removal filter. The performance analysis result depicts that ADTMF produces the better outcome both in qualitative and quantitative factors.

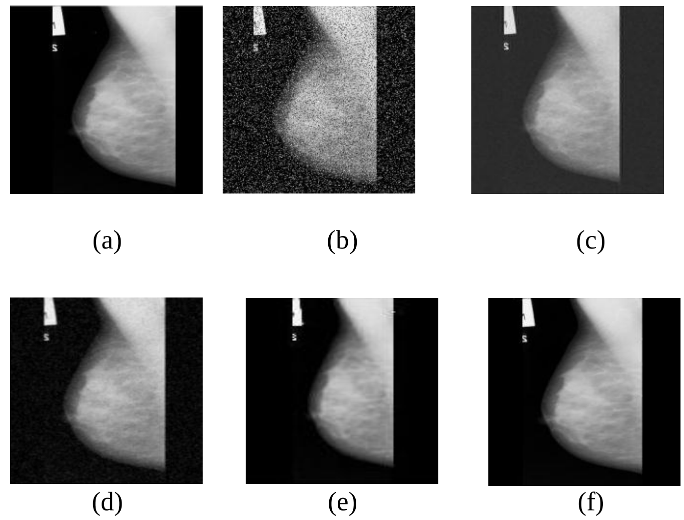

Figure 1. Denoised result of median based spatial filters (a) Original image (b) impulse noise corrupted image of 75% (c) DWMF (d) MDBUTMF (e) RAMF (f) ADTMF

From the visual result obtained from Figure 1, interprets how the two-stage algorithms are worked on the impulse noise mammogram images. Figure 1 (b) is the impulse noise corrupted image, here 75% of noise population is added to it. Figure 1 (c) is the DWMF result, it is observed from the visual result that many of the fine details are not clearly visible when compared to Figure 1(f). Figure 1(f) is the visual result of ADTMF and it is inferred from the visual result that significant fine details of the in the breast image are clearly visible and the noise pixels are accurately modified. The qualitative factors such as PSNR< MSE and SSIM are evaluated for these filter below in Table 1, 2, 3 respectively.

V. CONCLUSION AND FUTURE SCOPE

In this paper, the median based spatial filters for impulse noise is implemented for MIAS dataset. The denoising filters such as DWMF, MDBUTMF, RAMF and ADTMF were implemented to find their efficiency on impulse noise corrupted mammogram image. These median based denoising filters work well for the impulse noise and restore the corrupted image to a greater extent and that is shown in the result and performance section. The qualitative and quantitative factors such as PSNR, MSE and SSIM were used to evaluate the performance of the denoising filter.

Therefore, from the result and discussion, it is inferred that among these spatial filters ADTMF produces a better result when compared with the other existing filters and outcomes superiority in its performance.

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