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Impulse Noise Removal in Mammograms using Bi-Dimensional Empirical Mode Decomposition and Fast Adaptive Bilateral Filter

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***Abstract*: The work aims to detect and correct the noisy mammogram images corrupted by impulse noise. This is achieved in two phases – identification of noise-affected pixels and renovation of those pixels in an image. The pixels which are disturbed by impulse noise are identified by Bi-dimensional Empirical Mode Decomposition (Bid-EMD). The restoration of these pixels and noise removal are done by fast adaptive bilateral filter (fABF). The proposed work for impulse noise removal is examined on digital mammogram images of Digital Database for Screening Mammography (DDSM) database. The proposed approach is compared with other existing state-of-the-art schemes using peak signal to noise ratio (PSNR) and image enhancement factor (IEF) performance measures. The study of performance of the proposed scheme provides enhanced outcome than the other algorithms used for impulse noise removal.**

Index Terms: **breast cancer, empirical, fast bilateral, impulse noise, malignant, mammogram.**

I. INTRODUCTION

Breast cancer is the foremost reason of cancer death globally among females, subsequent to lung cancer. And it is the most general sort of cancer identified in females beside skin disease in the United States [1]. The effect of breast cancer is common for both male and female genders, but the disease is relatively infrequent in males. The death rate of breast cancer is progressively declining because of continuous research in earlier detection and a healthier understanding about the effect of illness. The cancer affected cells in human body reproduce more and starts to mount up, developing a lump (mass) than the unaffected cells do. These cancer affected cells forming lump may spread from the breast area to lymph area or other areas. The effect of breast cancer is more found on aged than the young females [2]. Based on the formation of lump in breast, the cancer is of two category namely benign and malignant type. Even though if there is lump or mass accumulated in breast cells are mentioned as a tumor, not every tumors are dangerous. The benign category of tumors are having the inability of spreading or affecting the surrounding breast cells, making it as a non-cancerous one. But in case of malignant type of disorder, the affected cells (lump or mass) can have the ability to influence the surrounding breast cells, making it as a cancerous one [3].

The digital mammogram is an imaging tool used to identify the breast cancer earlier. The source for the mammogram imaging formation is x-rays. This digital mammogram images is one of the tool for anterior identification of the disease for physicians [4]. For the assessment of the proposed scheme, the digital mammogram images are chosen from the DDSM - Digital Database for Screening Mammography dataset. The digital mammograms from this database is a popular source of promising usage by the mammographic image scrutiny research peoples. DDSM is a combined work among Sandia National, Massachusetts General and the University of South Florida. The DDSM comprises of about 2500 studies. Out of that, every individual study consist of 2 mammographic image analysis of respective breast with victim facts like age, breast density & subtlety rating and scanner & spatial information. Mammographic images available in the database with doubtful regions have related pixel-level statistics regarding the positions and categories of suspicious areas. The aim of the DDSM dataset is to make an improved study in the cancer research to assist in mammogram screening and to develop algorithms for the treatment of breast cancer [5]. Hence the abolition of noise in mammogram images is a vital one for the treatment of breast cancer. Impulse noise plays a key role in the degradation of mammogram images. The above said noise degrades the breast cancer images at the time of acquisition and communication. This noise is categorized into fixed-valued and random-valued type of impulse noise. If a noisy pixel may takes 0 (minimum) or 255 (maximum) as the pixel value, then it is termed as fixed-valued type. And if a noisy pixel might takes other random value lies in the range of 0 to 255, then it is stated as random-valued type [6]. In the last three decades of research in noise removal, numerous restoration algorithms by means of statistic filters (mean or median based) have been introduced for noise affected images [7]. But it is observed that only limited mechanisms were developed in the state-of-the-art workings on confiscation of the both types (fixed and random-valued) of impulse noise. The work in this paper, implements a novel methodology to detect and rectify the fixed-and-random valued type affected images. The restoration of noise affected medical (mammogram) images is done after the identification of fixed-and-random valued type impulse noise in the modality images. For the identification of noise corrupted pixels in the breast cancer images, the work utilizes the bi-dimensional empirical-mode decomposition mechanism and for the removal of same, the work makes use of fast-adaptive bilateral filter: this is exposed in fig. 1. The evaluation of the above said work is tested based on Peak signal to noise ratio (PSNR) and Correlation Factor (CF). The simulation results of the noise removal work corroborate the final outcome.

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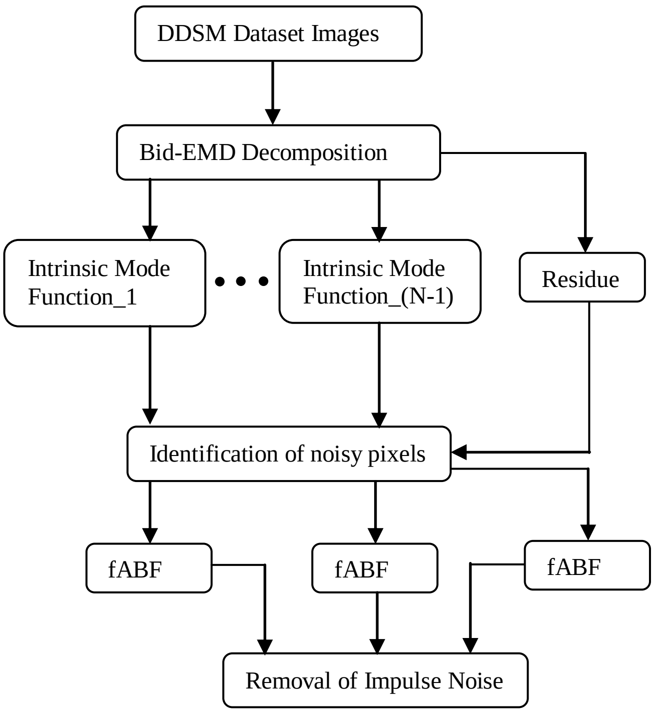


Fig. 1 Block Diagram of the Proposed Work

The structure of the manuscript is: The brief introduction on bi-dimensional empirical mode decomposition and fast adaptive bilateral filter is conferred in Section II. The Section III discuss about the proposed algorithm. The simulation outcomes and its performance analysis are given in Section IV. The conclusion of the work is discussed finally in Section V.

II. METHODS AND MATERIALS

A. *Bi-Dimensional Empirical Mode Decomposition*

Empirical Mode Decomposition, shortly EMD, is a type of empirical method to decompose any complicated signals (both stationary and non-stationary) of one-dimension or two-dimension. Its decomposition is similar to that of decomposition using wavelet or Fourier transform but not out of time-domain [8]. The concept of EMD is well thought-out to be oscillatory one at their each phase of confined oscillations. EMD is based on computing the IMFs - intrinsic mode functions, which are finite oscillatory components comprising the same amount of zero-crossings (finite) as extrema whereas these average minima and maxima nullify with each other [9]. Simply IMFs are the oscillating components that roll back-and-forth over the axis without having some static symmetry. These extracted IMFs are computed directly from the input signals during the decomposition. Thus EMD is an iterative algorithm extracting the IMFs with maximum frequencies and keeping the minimum time-series for the subsequent iteration and completing the process ensuring that the other time-series have not any IMFs. Every phase of the iteration initiates with developing an envelope by making the curves exactly fit with minima and maxima of the residual time-series [10]. The two-dimensional EMD is otherwise known as Bi-directional EMD (Bid-EMD) where the respective IMFs are extracted by means of "sifting" process [11]. As said earlier, this sifting process is done according to two conditions:

(a) every IMF has an equal amount of zero-crossings and extrema with corresponding symmetric envelopes and

(b) the obtained IMF considers that the input signal contains not less than two extrema (minimum and maximum).

And the procedure of this sifting process is as follows:

(i) Compute the local minima in the input data.

(ii) Link all these by means of a cubic-spline line as like as a maximum envelope.

(iii) Perform the above steps for the local minima to generate the minimum envelope.

B. *Fast Adaptive Bilateral Filter*

The non-linear means of bilateral filter is developed in 1998 by Tomasi and Manduchi [12]. This filter can able to smoothens (denoising) an image without affecting its strong edges. The filter preserves the fine points in an image during the denoising process. The bilateral filter customs a range kernel together with a spatial kernel and these two kernels are typically Gaussian [13]. This makes the bilateral filter to have applications in image denoising, edge enhancement, tone mapping and exposure correction in images. For the application of denoising in images, the conventional bilateral filter uses a static Gaussian-kind kernel laterally with a spatial-kernel for image smoothing together with edge preservation. The adaptive bilateral filter is the modification of conventional one in which the middle and width of the Gaussian-kind kernel is indorsed adaptively to vary from pixel-to-pixel whereas in the classical one, the middle and width of the Gaussian-kind kernel is fixed for all pixels in an image [14]. However this adaptive filter was initially developed for image sharpening, now can also be applied for removal of artifacts and noise in images. Analogous to the bilateral filter, the employment of its adaptive equivalent entails extreme computations. The adaptive bilateral filter is mathematically expressed as: Let the input image as $f: I \rightarrow R$ where $I \subset Z^2$ represents the spatial domain. Then the output $g: I \rightarrow R$ is

$$g(i) = \eta(i)^{-1} \sum_{j \epsilon \Omega} \omega(j) \phi_i\big(f(i-j) - \theta(i)\big) f(i-j) \qquad (1)$$

where

$$\eta(i) = \sum_{j \epsilon \Omega} \omega(j) \phi_i\big(f(i-j) - \theta(i)\big) \qquad (2)$$

The window Ω is of size $[-3\rho, +3\rho]^2$ centred at the middle part, ϕ_i represent the Gaussian range kernel and is denoted by

$$\phi_i(t) = \exp\left(-\frac{t^2}{2\sigma(i)^2}\right) \qquad (3)$$

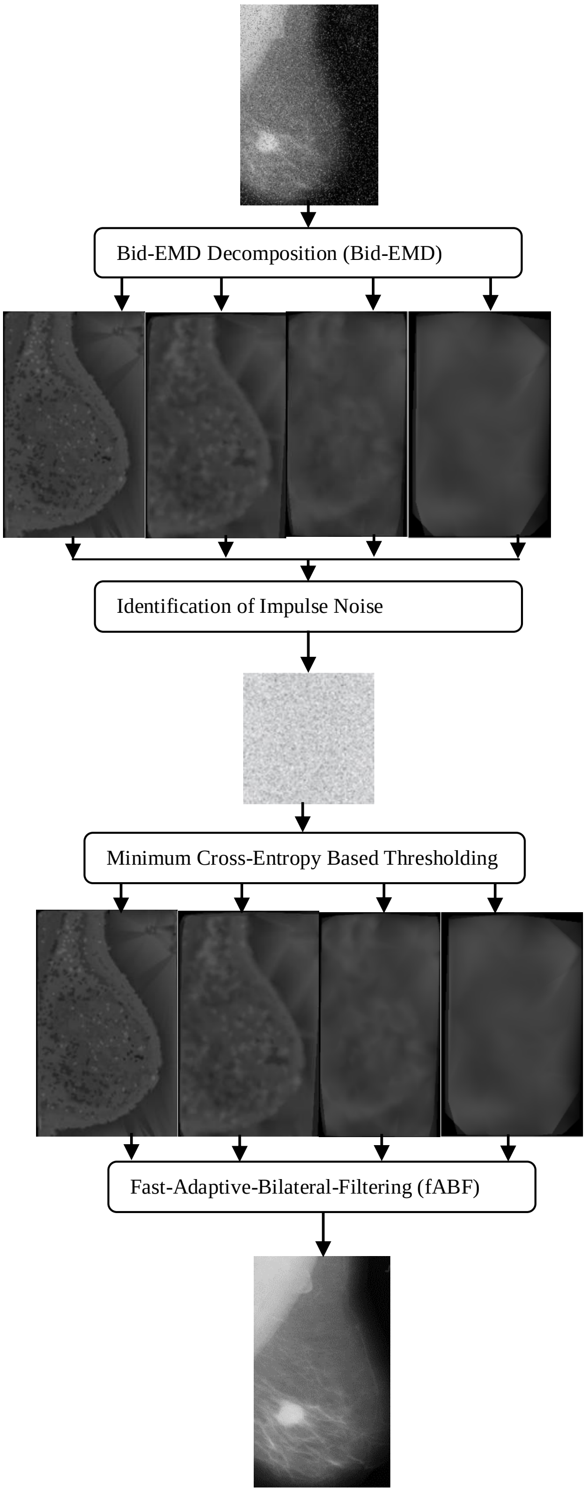


Fig. 2 Simulation Result at each stage of the Proposed Work

The $\theta(i)$representing centre in equation 1 and $\sigma(i)$denoting the width in equation 3 are meant to be spatially varying one. The Gaussian spatial kernel is $\omega(j)$denoted as

$$\omega(j) = \exp\left(-\frac{||j||^2}{2\rho^2}\right) \quad (4)$$

In equation 1 and 3, $\theta(i)$ and $\sigma(i)$ are needs to be vary for each pixels in an image; this makes the bilateral filter as an adaptive bilateral filter [15]. By acclimating the values of $\sigma(i)$at each pixel, the sharp edges are preserved in the images. Fast adaptive bilateral filtering involves the speedy algorithm for the reminiscent of equation 1 and make this to realize with any spatial kernel. Whatever the spatial kernel (either box or Gaussian), the per-pixel difficulty of the system is free of the taken window size [16]. Its brute-force implementation is accelerated to twenty percentage without compromising the quality of denoising.

III. PROPOSED METHOD

As in figure 1, the methodology starts with the identification of impulse noise in input images and retaining the original image without affecting its quality is done at the next step. The proposed method makes use of the Bid-EMD for the impulse noise pixel detection and fABF for the filtering of impulse noise with preserving the mammogram image quality. After the decomposition of original mammograms into IMFs by Bid-EMD way of decomposition, the statistical mean of the IMFs are taken for the noisy pixel identification. If the calculated mean is a smaller amount of the threshold, then the pixel is assigned as noisy whereas if the calculated mean is superior to the threshold, then the pixel is assigned as noise-free. This is denoted as 0 for noisy and 1 for noise-free. This intermediate step make use of one of the automatic thresholding method for the automatic selection of threshold value for the finding of impulse noise [17]. Several approaches for the selection of automatic threshold rely on the optimization of any discriminant function have been introduced [18]. These algorithms generally considers the distance based or similarity based metric concerning about the input image and the denoised result. This work utilizes a non-metric based, the minimum cross-entropy [19] for the calculation of the optimum threshold which is used to determine the impulse noise corrupted pixels. It is exposed that this way of threshold calculation is effective and easier one for finding the pixels which are corrupted by impulse noise in the extracted IMFs. This minimum cross-entropy based automatic threshold selection approach starts with the construction of a gray-level histogram and then the fitting of Gaussian densities is done [20]. Now the thresholds are automatically calculated as the cross-points based on these Gaussian densities. In this method, the two-dimensional histograms are utilized for the computation of threshold value [21]. This approach automatically identifies the number of noise corrupted pixels in the decomposed mammograms and is found to be effective for noise revealing in mammograms. This is exemplified clearly in fig. 2.

IV. RESULTS AND DISCUSSION

The evaluation of the proposed methodology is carried out using image denoising measures like PSNR and IEF. The proposed work is tested on the mammogram images of DDSM dataset. These simulation results are then compared with the (Standard Median Filter) SMF, (Adaptive Median Filter) AMF, (Bilateral Filter) BF and (Switching Bilateral Filter) SBF filters. Image enhancement or image denoising applications of any digital image outputs can be subjective (differ from person to person). Thus it is essential to develop quantitative measures for comparing the outputs of image denoising or enhancement techniques on image quality. PSNR is defined as the ratio between the highest probable rates (value) of a signal with the value of garbling noise that disturbs the image excellence for the representation [22]. PSNR is typically measured in the unit of logarithmic decibel measure, since most signals are having a wide-ranging dynamic range. In this work, by make use of DDSM dataset mammogram images, several image denoising filters can be compared analytically to recognize whether the proposed algorithm yields better outcomes or not. PSNR is defined as [23]

$$PSNR\ (dB) = 20\ log_{10}\left(\frac{255}{\sqrt{MSE}}\right) \qquad (5)$$

where

$$MSE = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}||f(i,j) - g(i,j)||^2 (6)$$

Table I. PSNR Values of Image_01 in the cancer_04 set in DDSM database.

Impulse Noise Density (%) / Schemes	10	30	50	70	90
SMF	31.51	23.69	15.38	10.16	6.54
AMF	40.14	33.82	29.56	25.58	17.21
BF	23.08	19.74	15.93	10.19	4.18
SBF	37.56	31.01	24.35	19.97	14.09
Proposed Method	40.48	34.55	31.72	28.61	21.66

Table II. IEF Values of Image_01 in the cancer_04 set in DDSM database.

Impulse Noise Density (%) / Schemes	10	30	50	70	90
SMF	14.88	13.57	4.39	1.86	1.12
AMF	76.54	70.51	49.73	31.08	13.61
BF	1.96	1.08	1.07	1.06	1.03
SBF	11.61	11.76	9.35	7.63	5.59
Proposed Method	182.37	134.84	85.78	55.59	25.34

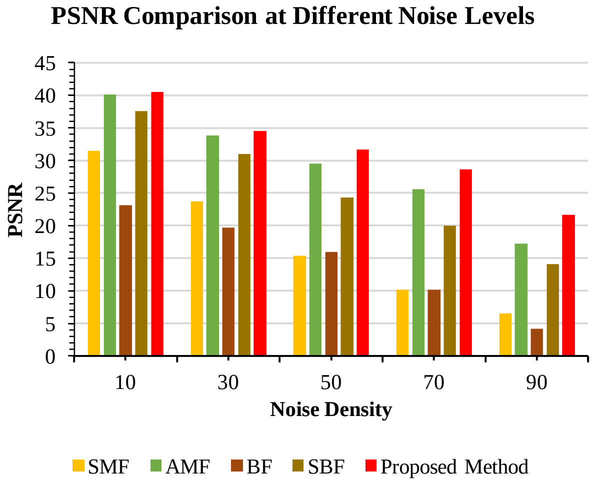


Fig. 3 PSNR Comparison at Different Noise Levels

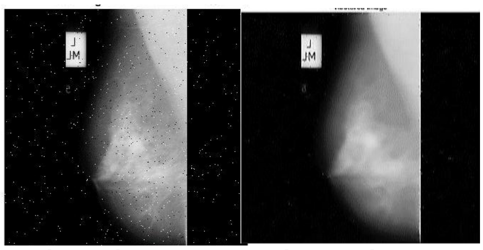
This MSE denotes the mean-square-error parameter and $f(i,j)$ represents the original and $g(i,j)$ denotes the noise removed image [24].

The IEF is a measure used to denote the ratio of MSE before filtering and MSE after filtering [25]. This is defined as

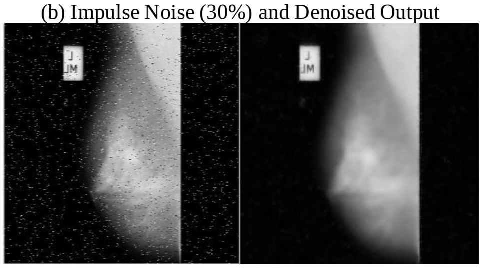
$$IEF = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N}(\eta(i,j)-g(i,j))^2}{\sum_{i=1}^{M}\sum_{j=1}^{N}(f(i,j)-g(i,j))^2} \qquad (7)$$

where η is the impulse noise affected image.

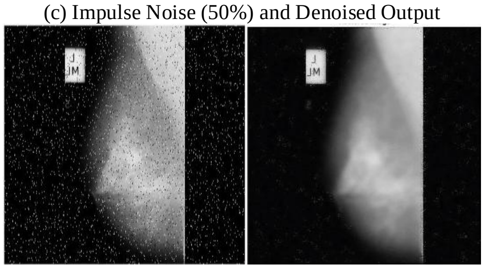
The Table I and II give the comparison of PSNR and IEF values for the Image_01 in the cancer_04 set in DDSM database. The taken mammogram image is of malignant type. This is graphically exposed in figure 3.



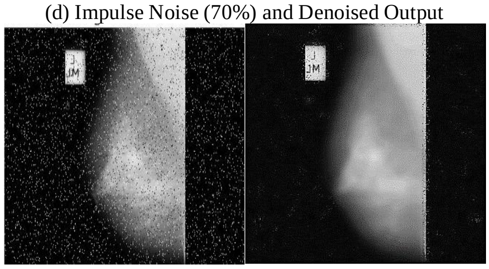
(a) Impulse Noise (10%) and Denoised Output



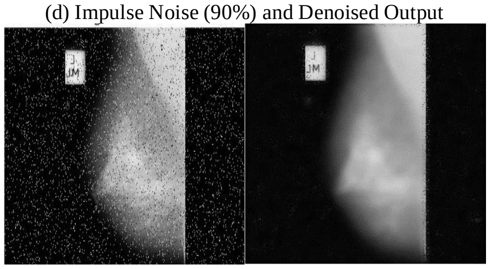
(b) Impulse Noise (30%) and Denoised Output



(c) Impulse Noise (50%) and Denoised Output



(d) Impulse Noise (70%) and Denoised Output



(d) Impulse Noise (90%) and Denoised Output

Fig. 3. Visual Analysis of the proposed method

The fig. 3 shows that the proposed method has a good result over others at noise levels ranging from 10 to 90 % of impulse noise. The average elapsed time for Bid-EMD decomposition of DDSM mammogram images is 0.981466 seconds and also the time taken for filtering the impulse noise is twenty percent faster than the standard bilateral filter. The performance of proposed method with 10 to 90 percent impulse density of Image_02 in the Cancer_04 set in DDSM database is shown in fig. 3.

V. CONCLUSION

The work implies a new noise removal approach to find and retain the mammograms degraded by the impulse noise. The implied method make use of bi-dimensional empirical mode decomposition to find the pixels spoiled by impulse noise. The mean of the extracted intrinsic mode functions are then related with the value of 2-dimensional minimum cross entropy threshold for finding the impulse noise troubled pixels. A fast-adaptive bilateral filter is utilized for retaining the corrupted pixels by impulse noise. The aim of using this faster adaptive bilateral filter at this point is to restore the fine details while simultaneously removing the noisy things in the medical mammograms. The work is carried out on various mammogram images in DDSM dataset. The performance of the work is tested by using the image quality metrics, Peak signal to noise ratio and Image Enhancement Factor. The final outcomes of the proposed work assert better noise removal than the existing noise removing techniques.

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