Performance Comparison of BFED Mammogram Restoration with Bilinear Filtering under Gaussian Noise

Rajesh Kochher[1*], Dr.Gagan Marken 2, Dr.Anshu Oberoi[3]

[1]*Research Scholor, Department of Computer Science, NIILM University, Haryana, India*

[2]*Assistant Professor, Department of Computer Science, NIILM University, Haryana, India*

[3]*HOD, Department of Computer Science , I.K.G Punjab Technical University Campus, Hoshiarpur, India*

ABSTRACT

The widely technique used for diagnosis of breast cancer is Mammography, where classification of masses is done using gray weighted function related to HSV color space based on statistical features. Noise in mammograms is a big issue during their diagnosis, so appropriate action have to be taken to remove the same. A large number of image restoration algorithm have been proposed to remove noise depend on the type of noise present in the image. In this work, we propose BFED method designed to reduce the Gaussian noise. The proposed filter is able to reduce image noise without any information loss from mammogram.

Keywords- Mammogram, Image Restoration, Gaussian Noise, BFED, BF.

I. INTRODUCTION

Medical imaging is the technique and process used to create images of the human body for clinical purposes and diagnosis (medical procedures seeking to reveal, diagnose or examine disease) or medical science [1]. Although imaging of removed organs and tissues can be performed for medical reasons, such procedures are not usually referred to as medical imaging [2][3]. As a discipline and in its widest sense, it is part of biological imaging and incorporates radiology, nuclear medicine, investigative radiological sciences, endoscopy, medical thermography, medical photography and microscopy [4]. Diagnostic radiography designates the technical aspects of medical imaging and in particular the acquisition of medical images. The radiographer or radiologic technologist is usually responsible for acquiring medical images of diagnostic quality, although some radiological interventions are performed by radiologists [5]. Medical imaging is often perceived to designate the set of techniques that non-invasively produce images of the internal aspect of the body. In this restricted sense, medical imaging can be seen as the solution of mathematical inverse problems. The term noninvasive is a term based on the fact that following medical imaging modalities do not penetrate the skin physically. But on the electromagnetic and radiation level, they are quite invasive [6]. Mammography provides the concept of utilizing low energy X-rays for finding of breast to locate the suspicious lesions. In order to for breast cancer detection, a beam of X-rays passes to each breast where it is absorbed by tissue for its density [2]. The remaining rays passes to a photographic film through the detector which produces a gray level image after its construction. The output

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image is known as film based mammogram, which is further send to make the film digitizer as shown in figure 1.

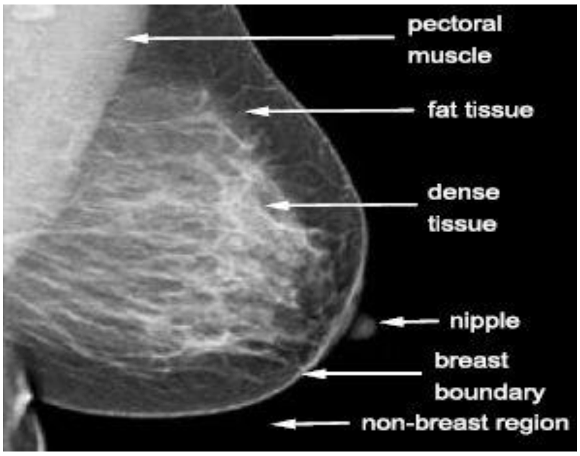

Fig. 1: Mammography Image [2]

The eminence in this research paper is given to experimental tentative estimation of Gaussian Noise on Mammograms Image Processing as digital image are mostly affected with those noises. Further BFED algorithm is used for mammogram restoration and its performance analysis is performed based on subjective observations. Image noise is the random variation of brightness or color information in images produced by the sensor and circuitry of a scanner or digital camera. Image noise can also originate in film grain and in the unavoidable shot noise of an ideal photon detector. Mathematically, Noise is represented by the percentage of the degraded pixels from the original image [2] and expressed as:

$$M(i,j) = P\begin{cases} N(i,j) & \text{with prob.} P \\ O(i,j) & \text{without prob.} 1-P \end{cases} \quad \dots\dots (i)$$

Where digital image M (i,j) is represents a as a sum of N(i,j) represents the noisy pixel &- O(i,j represents the noise free pixel [7].

Gaussian Noise consist the probability density function as the normal distribution so that the noise can take on Gaussian distribution over density function. It provides a well frequency spectrum for the Fourier transformation. . If the white noise sequence is a Gaussian sequence, then is called a white Gaussian noise (WGN) sequence. Gaussian Noise has a probability density function of the normal distribution and Probability density function is given as:

$$P(z) = \left(\frac{1}{\sqrt{2\pi\sigma}}\right) e^{-(z-\mu)^2} / 2\sigma^2$$

Where

$$\begin{cases} P = P_a \; for \; z = a \\ \quad P_b \; for \; z = b \\ 0 \quad otherwise \end{cases} \quad \dots\dots\dots\dots (ii)$$

Where z represents grey level, μ is average value of z, σ is standard deviation, σ^2 Is variance [8].

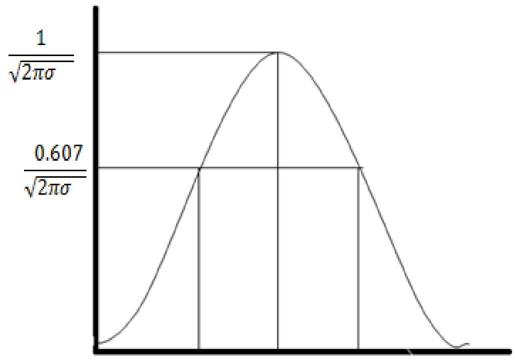

Fig. 2: PDF of Gaussian Noise

Bilateral Filter (BF) is a non-linear filter, which is more suitable for noise reducing of mammographic images. It works on the basis of intensity value of every pixel of images which are connected to other pixel and form a complete image. BF filter includes the weight of image in different environment such as color intensity and depth distance of pixels. The focus in this research paper is concentrated Mammogram Image restoration of Gaussian Noises corrupted mammograms using Bilateral Filtering & Euclidian Distance Classifier (BFED) noise removal algorithms. BFED is a nonlinear filtering method widely used for edge-preservation in image processing in which the intensity value at each pixel is evaluated as weighted average of its nearby pixels' intensity values [9]. BFED is proficient in setting up the problem of Mammogram Noise using Euclidean distance articulated below:

$$D(p) = K_p^{-1} \sum_{q \in R_p} W_s(d_{pq}) W_r(f_{pq}) I(q) \ldots\ldots\ldots\ldots\ldots iii$$

$$k_p = \sum_{q \in R_p} W_s(d_{pq}) W_r(f_{pq}) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots iv$$

where D(p) and I(q) denote the image intensities p of pixel in the output image and pixel q in the input image respectively. R_p represents a set of pixels neighboring to pixel p. and W_s and W_r are the spatial kernel and range kernel, for which the weights are computed from the Euclidean distance d_{pq} and the photometric difference f_{pq} between pixels p and q , respectively. The latter is usually measured by image features such as intensity or texture [10, 11]. K_p^{-1} is a normalization term computed by eqn. iii. Where in eqn. iv, Ws and W_r both take a value inverse to the corresponding input and are expressed typically as a Gaussian function. As an example, W_s is calculated by

$$W_s(d_{pq}) = e^{-(d_{pq}^2/2\sigma^2)} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots v$$

In eqn. v, d_{pq} is a scale parameter determining the weight distribution pattern of the kernel. The rest of the paper is organized as fallow; Section 2 describes brief literature survey on research done on different noise sources and their removal algorithms till date. In section 3 Gaussian Noise are implemented on a digital image and Noise removal algorithms are applied on it and their subjective analysis is performed and Section 4 conclude the paper.

II. LITERATURE SURVEY

A lot of research has been done in the field of image de-noising but yet the area of image de-noising, especially

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for the medical images remains to be a hot area of research. Stress has been laid to summarize the concept of different authors who has worked in this field. F. Chen et al., (2015) presented patch based image denoising method is developed in this paper by introducing a new type of image self-similarity. This self-similarity is obtained by cyclic shift, which is called circulant similarity. Given a corrupted image patch, it can be estimated by incorporating circulant similarity into a weighted averaging filter. H. Talebi, et al. (2014) presented a paradigm and developed for truly global filtering, where each pixel is estimated from all pixels in the image. Global filter can be implemented efficiently by sampling a fairly small percentage of the pixels in the image. PCA can discard a considerable part of noises without loss of signal information. Y. Zhang, et al. (2013) implemented an efficient image denoising scheme using PCA with LPG, which is a spatially adaptive image denoising scheme. PCA transformation matrix was used for the local window of images. A. Rajwade, et al. (2013) constructed to investigate the simple and elegant patch-based machine learning technique for image denoising using higher order singular value decomposition. J. Patil, et al. (2013) presented Evaluation and comparison between performances of modified denoising method and the local adaptive wavelet image denoising method. These methods are compared with PSNR between original image and noisy image and PSNR between original image and denoised image. W. Lui, et al. (2009) presented the concept of before denoising in which image's edges are first detected, and then the noised image is divided into two parts: edge part and smooth part. The theoretical analyses and experimental results presented in this paper show that, compared to commonly-used wavelet threshold denoising methods, the proposed algorithm could not only keep edge information of an image, but also could improve SNR the denoised image. G. Sanchez, et al. (2012) suggested medical image restoration with different types of noise. In this paper, X-ray and CT images has taken that may be contaminated with noise and performed detection of diseases. In this, they measured the performance of different noise using PGNDF technique on MIAS database. N. Browne, et al. (2016) presented a comprehensive strategy for mammogram image classification using learning classifier systems. In this paper, six types of statistical measures used for 3 different variants for local binary pattern, 10 variants for DWT. This paper also explained five different types of attributes in classifier conditions including individual statistical features, individual LBP features, concentration for LBP features, concentration with distances based DWT features, distances based LBP including DWT features to improve the classification accuracy. A. Alghaib, et al. (2016) explained an overview of mammogram analysis. In this paper, mammogram is an X-ray image of the human breast which is used for detection and diagnosis of changes in breast tissues. The images of women breast has taken on the basis of regular basis. These images were helpful for lesions for the detection which occur on a certain last age of cancer. M. Kumar, et al. (2016) presented detection of suspicious lesions in mammogram using fuzzy C-means algorithm. In this paper, small lump that are causes to lead breast cancer and can be detected at initial stage in mammogram. Sometimes mammography images have taken for small tumors including noisy and blurred fuzzy type images. For these types of detection FCM algorithm used to detect the suspicious lesions. S. Sushma, et al. (2016) suggested automated micro-calcification analysis using breast mammogram. In this paper early detection has done for mammography images for tumor detection and analysis and reduced the mortality rate for better enhancement. They used automatic segmentation without using training sequences. In this paper, contrast improvement index calculated for better enhancement. The presented research determines the existing system and analyse existing approach under corrupted mammograms due to Gaussian noise and mammogram restoration using Bilateral filter and Euclidian distance based hybrid approach for Image De-Noising to provide better results.

III. SYSTEM MODELLING

In this section, various noise models are implemented on mammographic image database, obtained from Digital Database for Screening Mammogram (DDSM) to conduct experiment. The mammogram's content can be accomplished by using four levels of gray. While describing the masses in mammogram they are enclosed with pixels with slight fluctuations in gray levels and configure smooth boundaries. Thus, it is very necessary to catch the boundary representation of the pixel values for segmentation of breast masses. The approach is conducted on spatial domain image processing with the use of HSV colour space properties and this color space is early relevant to human perception colors and for every pixel a weighted value is determined using a gray weighted function which seizes the gray part of the pixel and is very vigorous against noise and other noise parameters.

VI. RESULTS & DISCUSSIONS

The matrices used for analysis are as discussed; PSNR is ratio between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation. The PSNR of the noisy result is defined as follows:

$$PSNR = 10 \log \left\{ \frac{s^2}{\text{MSE}} \right\} \quad \dots\dots\dots\dots\dots\dots\dots vi$$

Where s = 255 for an 8-bit image. The PSNR is basically the SNR when all pixel values are equal to the maximum possible value. The Structural Similarity (SSIM) index is a method for measuring the similarity between two images. MSE is a commonly used reference based assessment metric is the Mean Square Error (MSE). The MSE between a noisy image, R, and a denoisy image, F, is given by the following equation:

$$MSE = \frac{1}{NM} * \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} e(m,n)^2 \quad \dots\dots\dots\dots vii$$

Where e(m, n) is the noisy (Mammographic) and M and N are image dimensions. Smaller the value of the MSE, better the performance of the fusion algorithm. SSIM (Similarity structural index value) depends on the psnr value and mse value. It is used to measure the quality of denoisy image according to the image restoration methods.

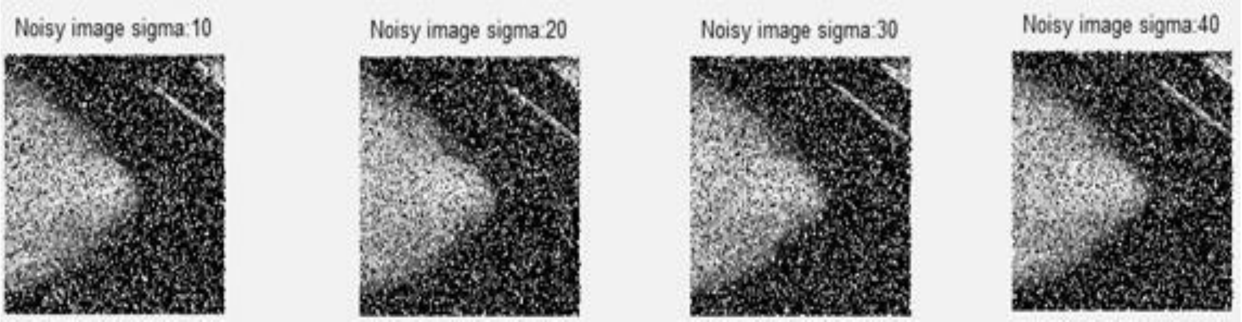

Fig. 3: Gaussian Noise Mammogram with varying S.D (σ) values

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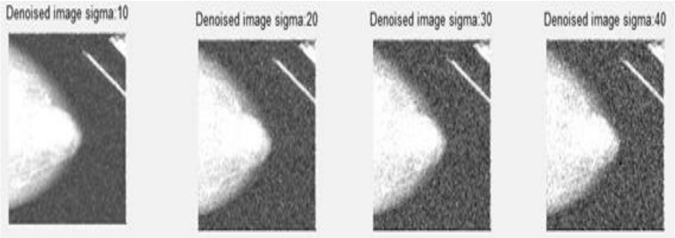

Fig. 4: BF based Denoised Gaussian Noise Mammogram with varying S.D

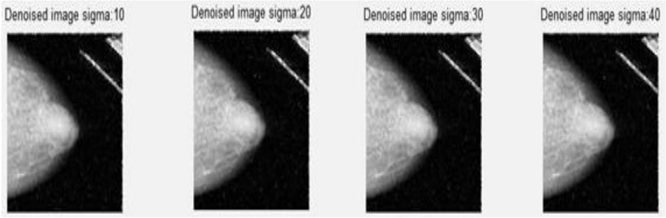

Fig. 5: BF based Denoised Gaussian Noise Mammogram with varying S.D (σ)

The mammogram image by means of Gaussian noise with varying standard deviation (σ) values is shown in figure 3, which depicts that with increase in σ the mammogram becomes more blur and noisy. Applying the BF and BFED filters to the mammogram with Gaussian Noise as shown in figure 4 and 5 respectively, it is observed subjectively the quality of the filtered mammogram with BFED filtering is better as compared to BF restoration technique.

TABLE I: MSE OF RESTORED MAMMOGRAM UNDER GAUSSIAN NOISE

METHOD	σ = 10	σ = 20	σ = 30	σ = 40
BFED Restoration	0.44	0.45	0.24	0.21
BF Restoration	0.66	0.66	0.46	0.47

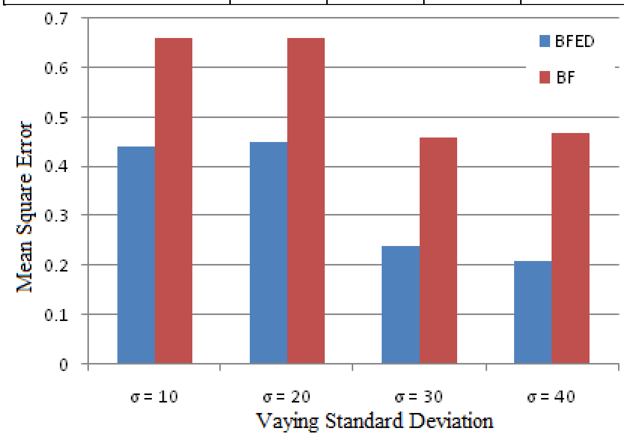

Fig. 6: MSE comparison of Denoised mammogram with varying S.D

Table 1 shows comparison between BFED and BF method for mse value. In this table BFED method provides low mse value as compared to bilinear filtering method. Therefore, BFED method is better for mammographic image at each standard deviation as shown in figure 6.

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TABLE II: PSNR OF RESTORED MAMMOGRAM UNDER GAUSSIAN NOISE

METHOD	σ = 10	σ = 20	σ = 30	σ = 40
BFED Restoration	68	65	64	65
BF Restoration	35	33	30	29

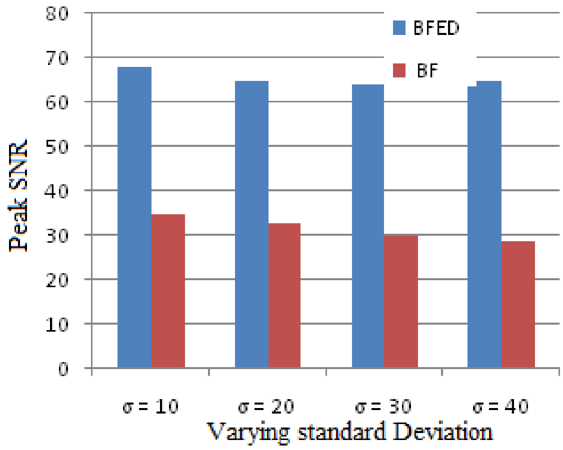

Fig. 7: PSNR comparison of Denoised mammogram with varying S.D

TABLE III: SSIM OF RESTORED MAMMOGRAM UNDER GAUSSIAN NOISE

METHOD	σ = 10	σ = 20	σ = 30	σ = 40
BFED Restoration	1.21	1.31	1.32	1.33
BF Restoration	0.94	0.90	0.86	0.77

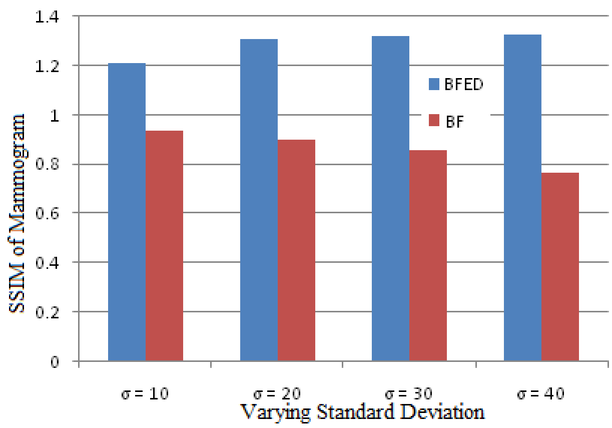

Fig. 8: SSIM comparison of Denoised mammogram with varying S.D

Table 2 shows comparison between BFED and PGFND method for psnr value. In this table the BFED method provides high psnr value as compared to BF method. Therefore, BFED method is better for mammographic image at each standard deviation as shown in figure 7. Table 3 shows comparison between BFED and BF method for SSIM value. The SSIM value is increasing at the each standard deviation. Therefore, Gaussian denoising is better in BFED for quality to mammographic image as shown in figure 8.

IV. CONCLUSION

This work emphasized on a mammogram restoration using BFED algorithm and its performance comparison with bilinear filter technique for mammograms under Gaussian noise. BFED outperforms Bilinear filtering technique in terms of MSE, PSNR and SSIM under implemented noise models. If the image contains only Gaussian noise, the best technique for removing noise has been the BFED algorithm, followed closely by the bilinear filtering method. We conclude that the BFED is the best suited algorithm when there is no information about the nature of the noise.

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