Noise Removal and Enhancement of Digital Mammographic Images for Visual Screening

Muhammad Hameed Siddiqi

Abstract**:** ***Cancer is one of the most dangerous diseases that if not diagnosed at early stages can lead to death. Cancer is of different types and breast cancer is a known form of it that is prevailing around the world. It is found in almost 11% of the world women population in their life time. The early detection of this type of cancer is essential not only to reduce the life fatalities but also for the human race. Due to some drawbacks and negative impacts, it remains a fascinating concern to recover the pictorial eminence of mammograms at the initial stage by a robust method to examine the cancer in the breast. In this study, we have presented a method of noise destruction and image enrichment by utilizing wavelet transform. The proposed method consisted of three steps. Also, the preprocessing was employed to improve the local divergence in condensed areas in which the improvement parameter delivers the anticipated aspect enrichment. In the proposed method, the effect of artifacts has been solved that is one of the critical issues now a day, which produces during the analyzing of the mammographic image. The proposed algorithm gave best results as compared to the existing works for which less user adjustment parameters are required.***

Keywords**:** ***Mammographic image, noise removal, wavelet transform, decomposition.***

I. INTRODUCTION

Various image-enhancing techniques exist in literature that focus on detection and diagnosis of cancer effects in images. Among them, Mammography is an efficient technique that has received enormous attention from the computer science community. Mammographic interpretation generated by computer-based methods are used in various analytical devices including visualization tools and second opinion devices. The visualization tools normally are used to assist domain experts and to improve the mammogram quality and the extraction of key information that may contain critical/hidden information /data. The second opinion devices/methods usually provide key information that can be used to identify probable pathological areas and beyond, and this information can be further used to characterize the abnormalities. Generally, a computer aided detection (CAD) method must contain several steps including preprocessing, segmentation, and classification, and they can be applied to on datasets for classification, e.g. to classify pathological cases. The preprocessing step in the CAD method is used to enhance the significant features of the mammogram, to recover the hidden information/properties and to improve the quality of images [1].

Traditionally, algorithms used to images focus on the enhancement of the divergence structures and the reduction of the clatter. These divergence structures enrichment methods initially exploit the difficulty function and/or other techniques including filters like morphological, band-pass, and detection filters [2,3]. Based on the parameters used by image enhancement techniques, one can classify them into local, global, and adaptive [4,5] techniques. The literature suggests that the preprocessing algorithms and the type of features exploit various methodologies including histogram equalization [4, 6-8], unsharp masking [6,9,10] region-based [3,11,12], wavelet decomposition [13-18], fractal modeling [19-22], and fuzzy methodology [23-26].

Despite a lot of advancement in the detection of film and resolution contrast, the screen film mammography still remains to be unfolded in depth especially for diagnostic imaging modality. Since the screen film mammography requires image interpretation which is a difficult process. Generally, breast radiographs examination includes investigation for the existence of malicious multitudes and other subsidiary symbols of malevolence including micro calcifications and skin thickening. Substantial efforts have been made to recover image recital; however, they focus mainly on-screen film radiography and it limits its functionality. In particular, the mammogram visualization displays a fraction of available information, and this deficiency is produced through the datum that there exist very little modifications in x-ray weakening among malignant and regular glandular materials [27]. The recognition of little distortions in younger women is a bit tough because they usually have thicker breast tissues whereas calcifications tend to have high weakening properties. The calcification tends to have these properties because of denser materials (same like bones); however, in size they are usually small and hence have very small/low local contrast. Therefore, these issues lead to the least accuracy of perceptibility of minor cancer and its connected micro calcifications – mainly in mammographic expertise on analog picture. It remains a concern to expand the pictorial superiority of mammograms to notice the chest cancer in the initial stages since they offer inherently low contrast regions and noisy regions. In summary, there are two main issues in enhancement of mammographic images: First is to improve the resident feature discrimination in different areas; while, the second one is to reduce noise in the images without introducing blur in satisfactory image specifics.

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In nuclear medicine, a high fraction of high occurrences is conquered through noise only, and not the signals. The generally used practices in this field apply morphological filters coupled with a gradient filter in order to expand signal to noise to ration. Nevertheless, the enhancement of SNR causes the image resolution to degrade because of the smoothness of high-resolution features [28]. Ideally, a desirable approach is to diminish the noise in reassembled picture over those areas wherever the features like high determination do not exist. This can be done using spatially-varying filtering method.

In this paper the author described the wavelet transform for denoising the mammographic images, because the Fourier techniques can effectively remove noise from indicators which are periodic globally are motionless because of the nature of its basic function (like the sinusoid). Where in frequency domain, sinusoid provides accurate localization and in space domain, no-localization. Since PET do not possess global and periodic behavior, and its signals are non-stationary, the properties of Fourier analysis do not offer the capability to remove noise from PET data [29]. Alternatively, in frequency and space domains, wavelets offer the ability to allow for combined resolution. Wavelets, in its basis, offer functions that are of finite duration and of changing ruler; therefore, making it conceivable to investigate indications at different determinations [30].

II. PROPOSED METHODOLOGY

The proposed methodology has been consisted of the following steps.

A. Preprocessing

Most of the X-ray images contain a lot of noise and random fluctuation, due to the statistical quantum absorption, which makes the detection of small and pervasive objects very hard to detect. Mostly the noise varies from image to image because the intensity in images and their noise have non-linear relationship.

In this paper a direct screening method [31] has been applied due to which they estimated local contrast with the help of the median of the neighborhood pixels intensities at *(i, j)* position. The local divergence is computed like

$$c(i,j) = f_n(i,j) - \mathrm{median}_e(i,j) \tag{1}$$

here *c (i, j)* indicates the projected local divergence, $f_n\ (i, j)$ shows the image gray level at *(i, j)* position, and *median (i, j)* represents the intermediate gray level between the locality at *(i, j).* The local contrast used to measure the high frequency noise that is a kind of high-pass filter. On every gray level *I* of the image, its associated noise might be calculated by the local divergence standard deviation $\sigma_c\ (I)$ which is the variability consideration of the entire pixels along with gray level *I*.

The noise is diminished by using the estimated local divergence standard deviation, for which they divide the image into the amount of containers, and for each container a separated local contrast standard deviation can be estimated (suppose each bin is indicated by "*x*", where *x*=1, 2, …., M). Once the noise has been diminished, the contrast enhancement function is estimated for each region, which is the ratio between the gray level variability $\sigma\ (I_i)$ and the local contrast standard deviation $\sigma_c\ (I_i)$.

B. Wavelet Transform

The sinusoid – the basis function of Fourier techniques makes it effective only at removing noise from signals that are globally periodic and stationary. As discussed earlier, in frequency domain, sinusoid provides accurate localization and in space domain, no-localization. So, to solve the negative impact of the Fourier techniques, the wavelet transform is used. The wavelet transform technique is one of the intelligent techniques for enhancement, which decompose the image into two coefficients called "Approximation" and "Detail" coefficients respectively. The general formula of the decomposition is given as:

$$X = A + D \tag{2}$$

Here, '*X*' denotes the decomposed image, *A* and *D* represent the coefficient vectors of approximation and detailed respectively. When the image can be divided into multiple levels, then the equation 1 might be written as:

$$X = A_i + D_i + D_{i-1} + D_{i-1} + \cdots + D_2 + D_1 \tag{3}$$

Here, *i* indicates the division level. Commonly, the D (detail) coefficients contains noise, and the approximation coefficients contains features of the original that can be used for further processing (depends on the application). Mostly, the image is decomposed up to three levels, so the value of *i* = 3. The detail coefficients at each level are further consisted of two sub-coefficients. So, the Equation.3 can be modified as:

$$X = A_3 + D_3 + D_2 + D_1 \tag{4}$$

This in fact shows that all the coefficients are connected with each other in the form of a chain. For more details, please refer [34]. It is obvious from the afore-mentioned equations that all the coefficients are connected with each other in the form of a chain just like the head to tail rule can be performed in a vector addition. The detailed coefficient vectors and approximation vectors are obtained during the decomposition process. In this process, the approximation coefficients are obtained by utilizing low-pass filter convolution; while, the detail coefficient are attained by employing the high-pass filter, and this process is called wavelet shrinking. In Fig. 1, we exemplify the decomposition of a 2D image and his corresponding coefficients.

Fig. 1 indicates the decomposition of the 2D image and their corresponding coefficients. It is obvious that the detail coefficients also included three other coefficients such as horizontal, diagonal and vertical coefficients. These coefficients mostly consisted of noise.

C. Image Denoising and Enhancement

Wavelet shrinking is one of the most usable methods that can be used in process that remove or reduce noise in data in which the presence of non-linearity in wavelet coefficients is unavoidable.

Because the non-linearity tends to reduce the low amplitude and retain the high amplitude values. Therefore, for every level (i.e. bin) no-negative and non-decreasing function has been founded due to which the wavelet coefficients will be updated that will further used for image enhancement, so for this the following rule has been defined:

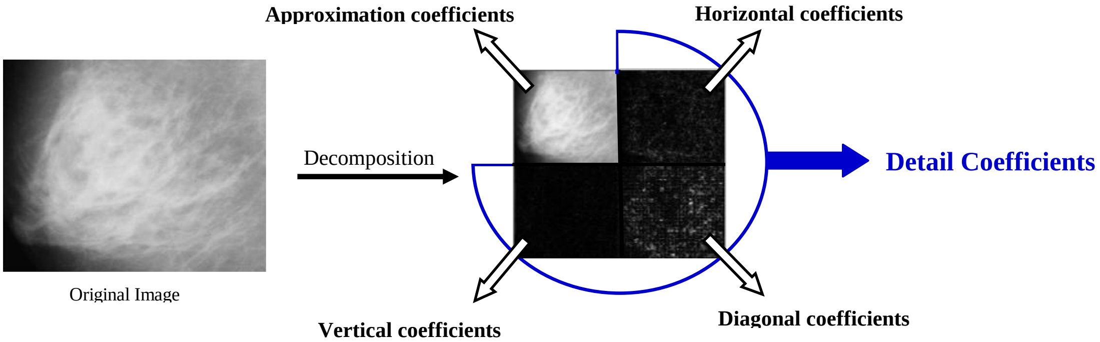

Fig. 1. Mammographic Image decomposition and its corresponding coefficients using Wavelet Transform

$$NW^{i}_{2j} f\,[i,j] = W^{i}_{2j} f\,(i,j)\; g^{i}_{j}\,[i,j],\; i = 1,2 \tag{5}$$

where $g^{i}_{j}\,[i,j] = g^{i}_{j}\,(W^{i}_{2j} f\,[i,j]$ indicate wavelet shrinking. So, this wavelet shrinking will be applied on the image scale and the sub-bands of the wavelet decomposition, when it necessary. It is to be noted that the modeled noise in this work for mammographic images is an adoptive zero mean Gaussian noise. Therefore, the details of a coefficient of an image is primarily given by the Gaussian noise, which is considered as Gaussian distributed with standard deviation σ_N. In the preprocessing step, the use of contrast enhancement algorithm conserves the noise Gaussianity.

$$p(I|N) = \frac{1}{\sigma_N\sqrt{2\pi}}\, e^{-I^{2}/2\sigma_N^{2}} \tag{6}$$

where $p(I|N)$ indicates the coefficients distribution with the assumption that the image only contains noise. It should also be noted here that the wavelet coefficients distribute sharply and reach its peak near origin for noise free images due the homogeneous regions that possess long tails, also called edges. The most suitable model that can be used to model this type of coefficients Generalized Laplacian probability density function that is used for noise spreading for free image wavelet coefficients as presented in Fig.2.

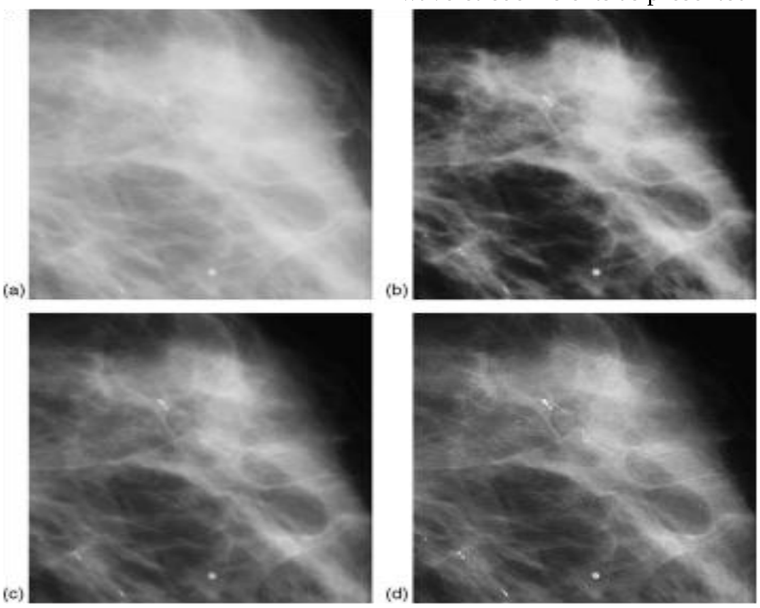

Fig.2. (a) Initial image; (b) image enhancement through histogram equalization; (c) result of the designed approach; and (d) denoising and enhancing result (microcalcifications features are observable that are situated in condensed tissue).

The main objective of the proposed approach is to model the spreading of the generic factors of the images that contain deafening edges and consistent areas disturbed by noise, and which are also approximated by the Gaussian and Generalized Laplacian distributions. If the image has Gaussian noise, then the coefficients that are related to edges will not be significantly affected because mostly the edges have high magnitude than the coefficients that are related to noise.

The main reason is for this is that, in this paper, the coefficients that belong to the end of the spreading are more like selected superiority related, and the factors that are near the base of histogram that are closer/associated to noise (and ultimately near the consistent areas). Therefore, the base of histogram i.e. origin will tend to of the Gaussian shape, the end of the spreading follows the general Laplacian function, and the entire spreading for the $Wf\,[i, j]$ coupled with noise and edge factors is described as:

$$p(I) = wp\,(I|N) + (1 - w)\,p(I|E) \quad (7)$$

here the unidentified constraint of the entire factor distribution is indicated by w, and the value of which will be between 0 and 1, and E represents an edge. Sometimes the wavelet coefficients examination does not present enough judgement among edge and noise-related factors where we determine the maximum noise pollution. A better and visible judgement might be obtained through the analysis of existing evidences in various scales. Generally, the reliability on various scales is investigated by calculating the Lipschitz proponent for wavelet factors [8] or by shortest factors' relation in successive scales [24, 25].

In the proposed study, we investigate the reliability on various scales through a simple method i.e. by shrinking the parameters in head-to-head scales [26].

III. EXPERIMENTAL RESULTS

As stated above, the technique to remove noise might be prolonged resident contrast improvement nearby boundaries. The lined improvement is an easy and simple, and it might be attained by letting the shrinking parameters $g^{scale}_{x}\,[i, j] > 1$ such that the resident contrast can be improved nearby the boundaries. Nonetheless, the lined improvement mostly inclines to highlight on more robust boundaries and mammograms. These are in fact improved by a lined factor that contains a clear concentration macrocalcification, which results in uncivilized rescaling along with the existing lively series for presenting the images [2]. The de-noising result of the mammographic image and the divided bins in the form of cumulative histogram is given in Fig.3. Some other sample results of the proposed methods on different level decomposition are shown in Fig. 4, 5, 6, and 7 respectively.

As can be seen from the Fig. 3, 4, 5, 6, and 7 that the proposed method significantly reduced the noise from the images and robustly enhance the images against existing methods.

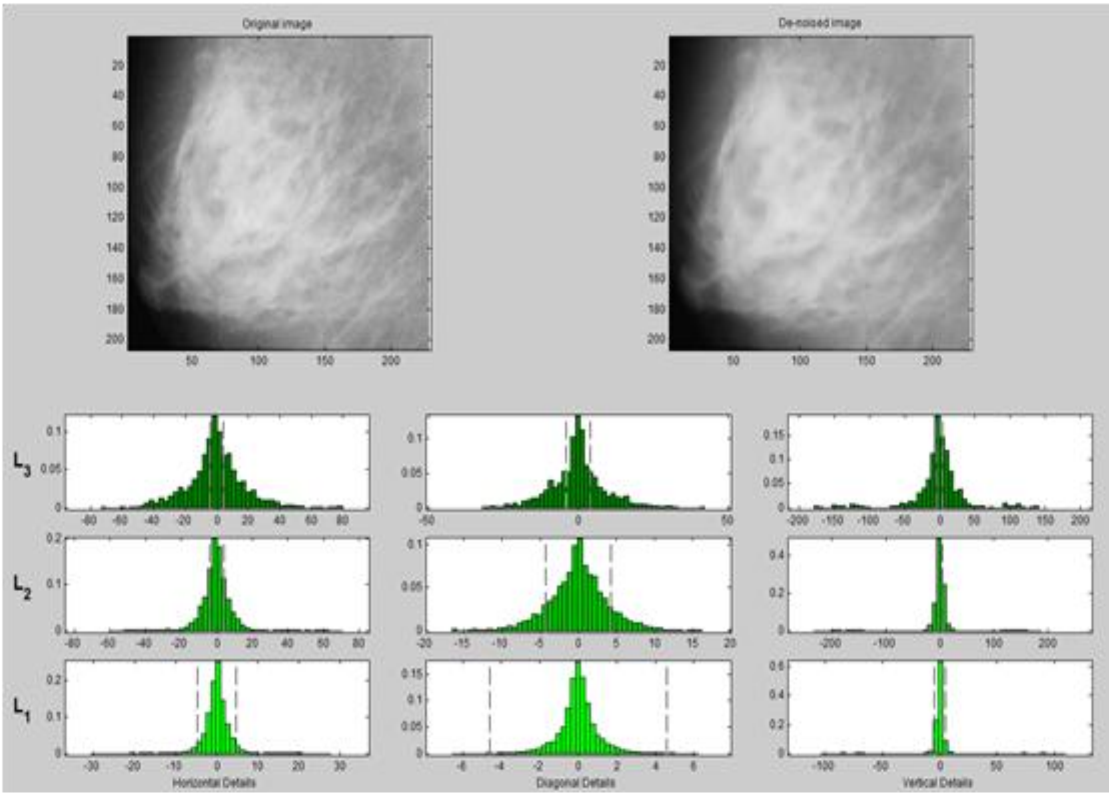

Fig. 3: de-noising result of the mammographic image and the divided bins in the form of cumulative histogram.

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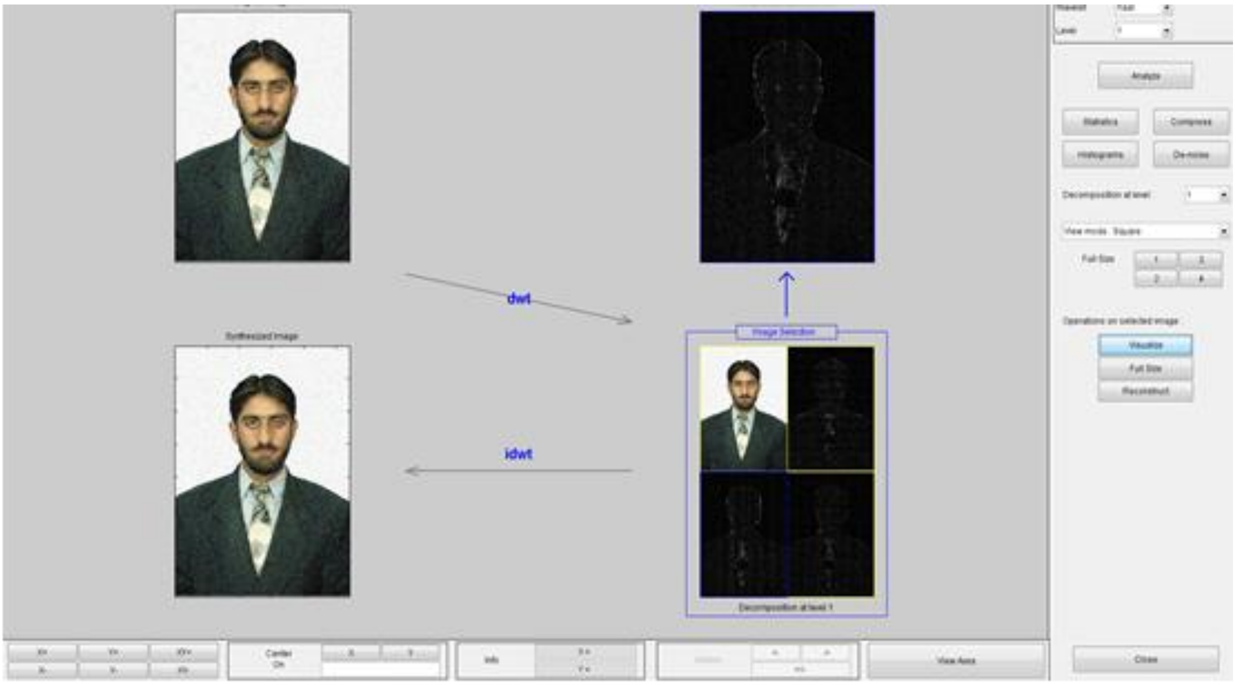

Fig. 4: Sample result of the proposed method at first level of decomposition after employing wavelet transform.

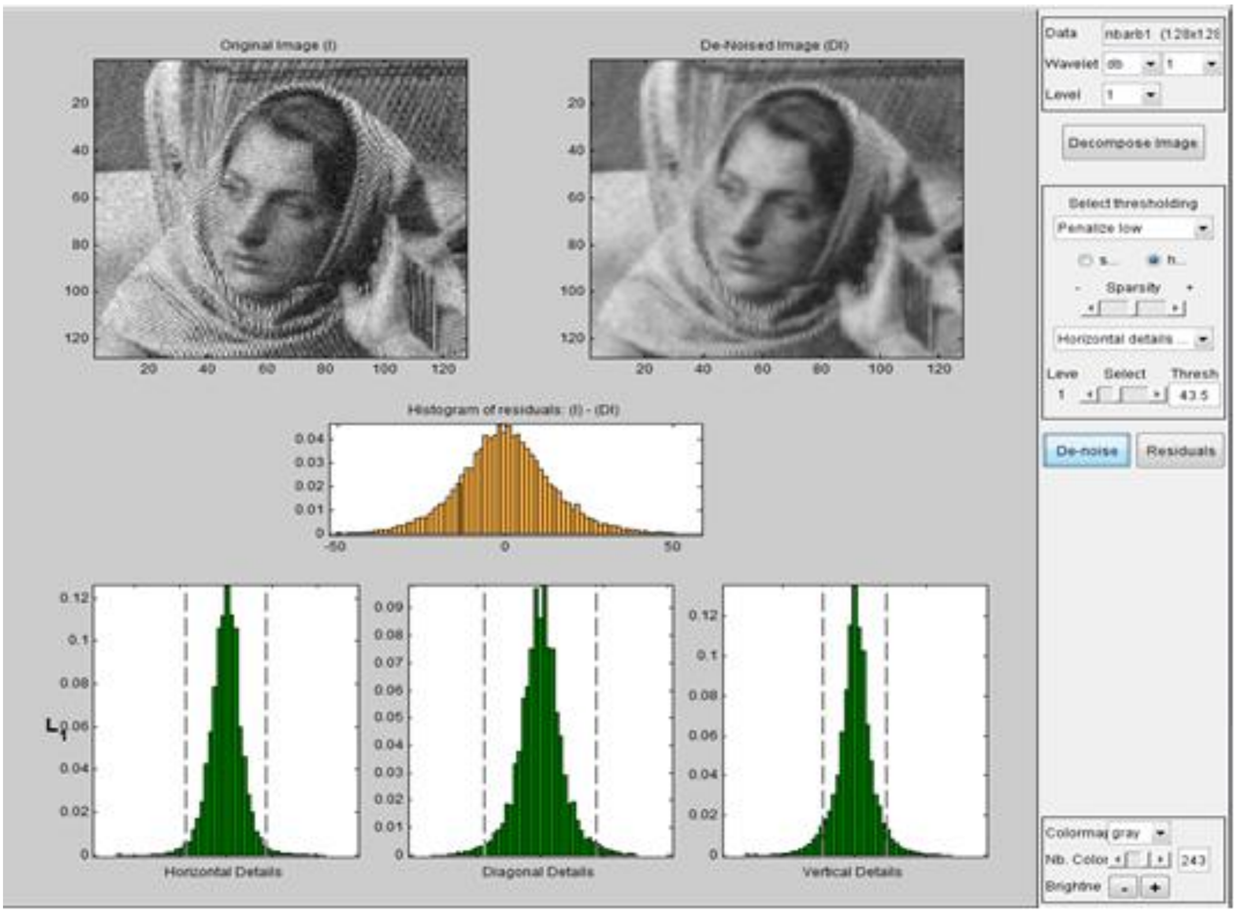

Fig. 5: Sample image of de-noising that are divided into number of bins to form cumulative histogram at one level decomposition.

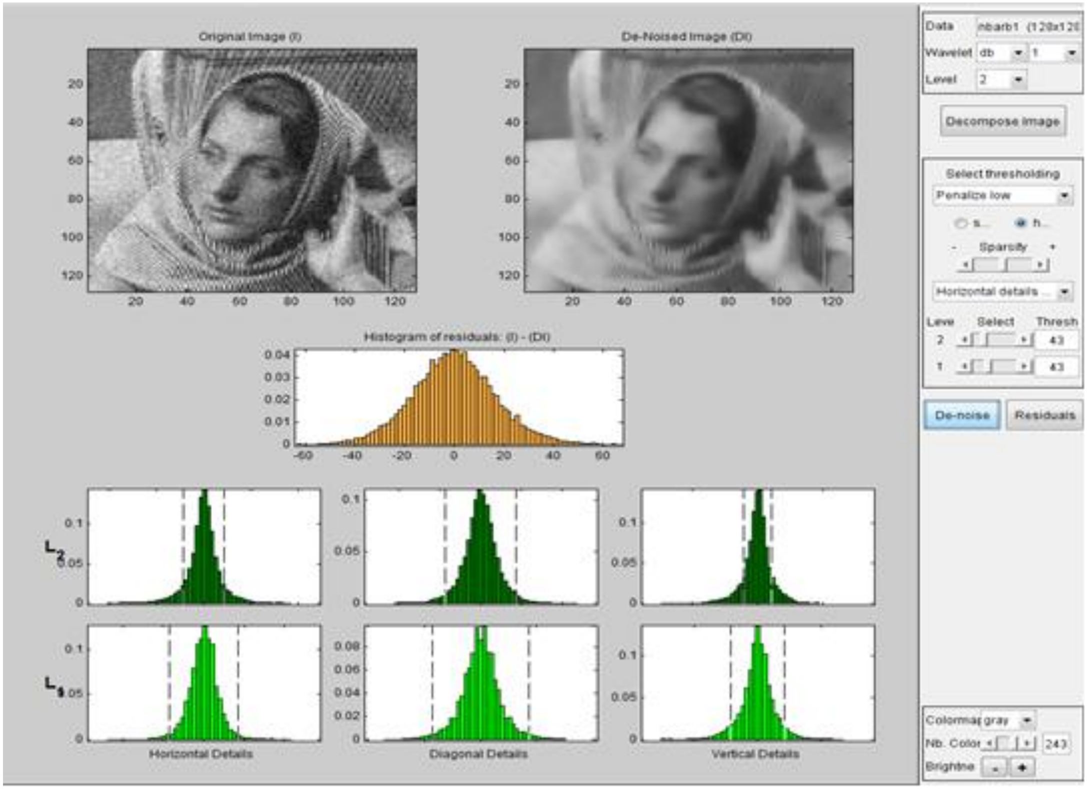

Fig. 6: Sample image of de-noising that are divided into number of bins to form cumulative histogram at two level decomposition.

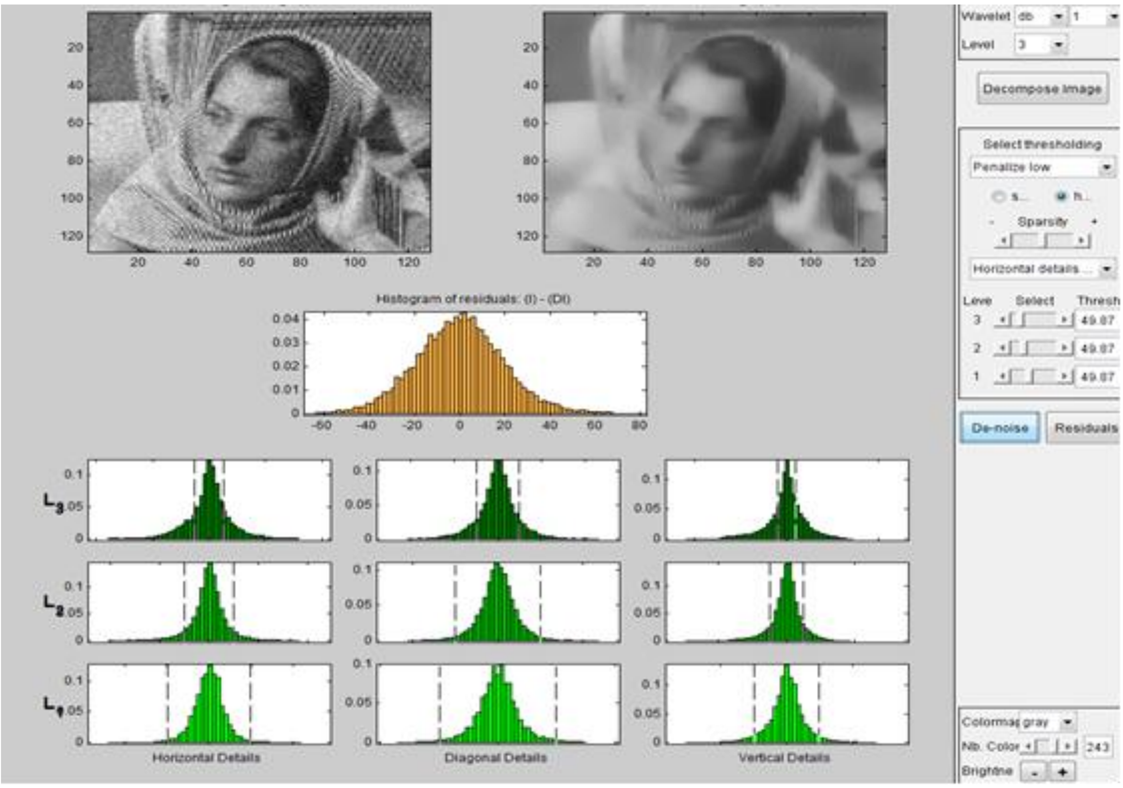

Fig. 7: Sample image of de-noising that are divided into number of bins to form cumulative histogram at three level decomposition.

IV. CONCLUSION

Cancer is one of the most dangerous diseases that if not diagnosed at early stages can lead to death. Cancer is of different types and breast cancer is a known form of it that is prevailing around the world. It is found in almost 11% of the world women population in their whole life. The world health organization (WHO)'s agency for Research on Cancer (IARC) estimates show that over a million cases of breast cancer will happen annually (worldwide), and that over 400 thousand women will probably die every year from this disease if not taken care of [32]. The initial detection of this type of cancer is essential not only to reduce the life fatalities but also for the human race [33]. Due to some drawbacks and negative impacts, it remains a fascinating concern to recover the pictorial eminence of mammograms at the initial stage by a robust method to examine the cancer in the breast. In this study, we have presented a method of noise destruction and image enrichment by utilizing wavelet transform. The proposed method consisted of three steps. Also, the preprocessing was employed to improve the local divergence in condensed areas in which the improvement parameter delivers the anticipated aspect enrichment. In the proposed method, the effect of artifacts has been solved that is one of the critical issues now a day, which produces during the analyzing of the mammographic image. The proposed algorithm gave best results as compared to the existing works for which less user adjustment parameters are required. In the future work, we will plane to evaluate our approach in clinical trials that are designed by mammography specialists.

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