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EFFICIENT EDGE EMPHASIZED MAMMOGRAM IMAGE ENHANCEMENT FOR DETECTION OF MICROCALCIFICATION

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ABSTRACT

An efficient detection of microcalcification based on edge enhancement using discrete wavelet transform (DWT) is presented in this paper. The proposed method is implemented by separating the wavelet coefficients into weak and strong edge coefficients for effective detection of microcalcification. Identification of strong and weak edge locations corresponding to microcalcification is obtained by allowing the input image through appropriate filters before wavelet decomposition. Before reconstructing the output image, the strong and weak edge coefficients are modified based on the energy of the coefficients. The reconstructed image exhibits a better enhancement with the fine detail components of microcalcification than the original mammogram image. Standard Mias mammogram database images and clinical mammograms are used for testing and comparing subjective and objective measures of the mammogram images. A comparative study is made with the existing state-of-the-art edge enhancement and contrast enhancement methods and results are encouraging. The edge emphasizing ability of the proposed method is highly proficient in detection of microcalcification from the mammogram.

Keywords: Edge enhancement; Detection of microcalcification; Weak and strong edges; Discrete wavelet transform (DWT-EE); Measure of Enhancement (EME).

INTRODUCTION

Breast Cancer is the second leading cause of death for women and is expected to become the leading cause of death in the near future. Microcalcification, milk ducts are small in size and is an early stage of premier indication of abnormality in mammograms. Early detection of breast cancer in the mammograms is very essential in the field of medicine. Mammography is the primary imaging technique for the detection and diagnosis of breast lesions. However, mammographers miss about 10% of all cancerous lesions. Also, the overall percentage of breast cancer detected per number of breast biopsies performed on the basis of mammography screening ranges between 10% and 50%.[1] These high miss and high false-positive rates are caused by the low contrast and noisy nature of the images, as well as the overlying and underlying structures in the projection radiograph that obscure features of interest. Several computer-based algorithms have been proposed to enhance the subtle features of interest in the mammogram image and it has created a big field for research.

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Image enhancement of mammography is the fundamental need of hour today. Difference in contrast between malignant tissue (abnormal) and normal dense tissue may be present on a mammogram, but below the threshold of human perception.[2] The paper is to provide an enhanced mammogram with a better indication of the presence of microcalcification. Contrast enhancement methods like adaptive histogram equalization (AHE) and contrast limited adaptive histogram equalization (CLAHE) are effective image enhancement techniques in the literature. But they usually provide an excessive enhancement in the output image. These methods do not concentrate on frequency components of the given image. In the past, many image enhancement approaches with the principle of AHE was proposed.[3–7] In those researches, there were some problems in reducing the mean brightness in the output image. The reduction in mean brightness hides the detail components and microcalcification of the image. Adaptive unsharp masking,[8] a frequency selective method, was also applied for image contrast enhancement. But it also suffers to detect low contrast edges present in the input image. Dhawan and Gordon have done a research on mammograms for its contrast enhancement and for identification of image features associated with breast cancer.[9,10] Adaptive neighborhood method is adopted by them to enhance mammogram features, but it is sensitive to noise. Rangayyan *et al.*'s work on mammography improved to a very good extent, but its time complexity was more.[11]

Mammogram contrast enhancement using wavelet-based methods, an alternative way in frequency domain processing, resulted in improving the preservation of details of mammogram image,[12] but it also suffers from noise in the input image. Kim *et al.* proposed a method for mammographic image enhancement using first derivative and local statistics.[13] This method was suitable for low degree of gray level discontinuities in the mammogram images. Partitioned iterated function systems (PIFS), a contrast enhancement proposed by Economopoulos *et al.*[14] is also tested for mammogram image enhancement, but it gave more artifact, irrelevant details, as the method concentrated more on local processing. More researches are going on detection of microcalcification, but there is still a problem of obtaining contrast enhancement and edge enhancement, without the loss of subtle information or artifact. The CLAHE introduced by Zuiderveld had shown a good result in image contrast enhancement[15] and, when it was used for testing medical images, it produceed excessive enhancement. The excessive enhancement will either lead to washing out the available edges in the image or make artifacts in the image. Histogram modified local contrast enhancement for mammogram images (HM-LCE)[16] reduced excessive enhancement in the output mammogram image. But it also suffers in need of a post-processing for the detection of microcalcification after the enhancement is over. In the literature, the wavelet coefficients are grouped into weak and strong edges based on the magnitude of the coefficients. But the proposed method focuses on weak and strong edges, especially the microcalcifications belong to high frequency are managed in a special approach. The weak edges are the microcalcifications within low contrast region inside the original image and strong edges are the microcalcifications having considerable contrast in the image. An effective edge enhancement technique should be able to identify both the types of edges to get meaningful information from the output image. In the proposed method, identification of location of strong and weak edges is obtained to have efficient representation of microcalcifications by this new edge enhancement method. Detailed explanation of methodology including the algorithm is given in "Materials and Methods" section regarding the separation of strong and weak edges. "Results" section deals with results and discussion to analyze the effectiveness of the method in representing the microcalcification, while "Discussion" section presents conclusion of this edge emphasized method for detection of microcalcification in mammograms.

MATERIALS AND METHODS

2D-Discrete Wavelet Transform Based Edge Emphasized Mammogram Image Enhancement (DWT-EE)

CLAHE and HM-LCE provide better image contrast enhancement for given mammogram image. But, it is necessary to have further post-processing of the enhanced images in order to get information on microcalcification. These methods do not concentrate on frequency components of the image. If the frequency component of the mammogram image is considered for detection of microcalcification, it will be more effective for detection of microcalcification. Wavelet-based method is a frequency domain process and it is more efficient in detecting edges, high frequency component, in the image. The paper is proposed for emphasizing the edges in the mammogram images using discrete wavelet transform (DWT). It decomposes the image into wavelet coefficients and separates weak and strong edges in the mammogram image. Then the coefficients are mapped according to a nonlinear enhancement parameter in order to emphasize the edges, microcalcification, in the mammograms before reconstruction of the output image.

Discrete Wavelet Transforms

The field of DWT is an amazingly recent one. The basic principles of wavelet theory were put forth in a paper by Gabor in 1945. A wavelet, in the sense of the DWT, is an orthogonal function which can be applied to a finite group of data. Functionally, it is very much like the discrete Fourier transform (DFT), in that the transforming function is orthogonal, a signal passed twice through the transformation is unchanged, and the input signal is assumed to be a set of discrete-time samples. Both transforms are convolutions. These convolution functions are filters; one half of the output is produced by the "low-pass" filter function, related to Eq. (1):

$$a_i = \frac{1}{2}\sum_{j=1}^{N} C_{2i-j+1} f_j \quad i = 1, 2, \ldots, N/2 \tag{1}$$

and other half is produced by the "high-pass" filter function, related to Eq. (2):

$$b_i = \frac{1}{2}\sum_{j=1}^{N} (-1)^{j+1} C_{j+2-2i} f_j \quad i = 1, 2, 3, \ldots, N/2, \tag{2}$$

where N is the input block size, C are the Coefficients, f is the input function, and a and b are the output functions.

The Haar wavelet is very simple and effective and it is used in this application. After passing the data through the filter functions, the output of the low-pass filter consists of the average of every two samples, and the output of the high-pass filter consists of the difference of every two samples. High-pass filter obviously contains less information than the low-pass output. If the signal is reconstructed by an inverse low-pass filter of the form as shown in Eq. (3)

$$f_j^L = \sum_{i=1}^{N/2} C_{2i-j} a_i \quad j = 1, 2, \ldots, N \tag{3}$$

then the result is a duplication of each entry from the low-pass filter output. The result of the inverse high-pass filter function is obtained using Eq. (4).

$$f_j^H = \sum_{i=1}^{N/2} (-1)^{j+1} C_{j+1-2i} b_i \quad j = 1, 2, \ldots, N. \tag{4}$$

The perfectly reconstructed signal is obtained by using the Eq. (5).

$$f = f^L + f^H. \tag{5}$$

The above equations are given for one-dimensional signal, but the same procedure is also applicable for images, two-dimensional function. DWT has been used as a basis of many multi scale enhancement methods. It offers several advantages over other orthogonal wavelet transforms, mainly, lack of aliasing, smooth and symmetrical basis functions and multi scale gradient computation. DWT leads to a decomposition of approximation co-efficient, low frequency components, at level j in four components namely the approximation at level $j+1$ and the details, high frequency components, in three orientations, horizontal, vertical and diagonal.

The steps involved in the proposal method is described as follows

Step 1: Noises are removed from the original image.

Step 2: (a) Applying Average filter to get the location of strong edges in the sub-bands.
(b) Applying unsharp marking to get the location of weak edges.

Step 3: (a) Applying DWT to the image obtained in step 2(a).
(b) Applying DWT to the image obtained in step 2(b).

Step 4: (a) Location of nonzero coefficients in the sub-band of step 3(a) are registered as location of strong edges.
(b) Location of nonzero coefficients in the sub-band for step 3(b) are registered as location of weak edges.

Step 5: Step 4 is applied for all sub-bands and making a group of table of weak and strong edges for all sub-bands.

Step 6: Applying DWT for image obtained in step 1.

Step 7: The coefficients obtained in step 6 are correlated with location table and they are mapped by Eq. (9) according to the labeling as strong and weak edges.

Step 8: Modified sub-band coefficients are used for reconstructions of output image which brings microcalcification as visible.

In the proposed method as shown in the block diagram of Fig. 1, after removing the noise from the input image,[13] identification of location of strong and weak edges is done by this new approach. In order to identify the strong edges in the mammogram, the input image is passed through a median or average filter before applying 2D DWT decomposition. The paper uses weighted average filter, as shown in Fig. 2, for the process of detecting the location of strong edges. This process of identification of location of strong edges is called as channel-1 processing. By applying average filter before wavelet decomposition, the weak edges are suppressed more than the strong edges. Now the wavelet decomposition gives only

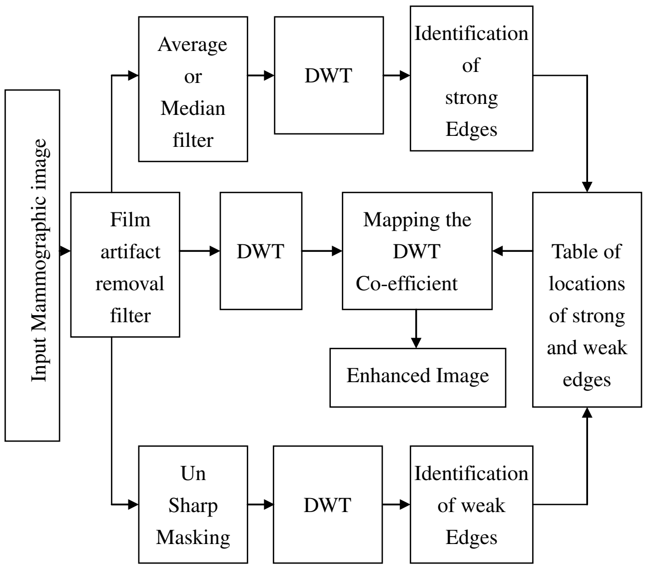


Fig. 1 Block diagram of the proposed method.

coefficients related to strong edges. Then locations having nonzero coefficients are registered as location of strong edges. Detecting the location of week edges is achieved by applying unsharp masking filter before wavelet decomposition. This process of selection of location of weak edges is called channel-2 processing. In general, the unsharp masked image $g(x, y)$ is represented by the following Eq. (6).

$$g(x, y) = f(x, y) + \bar{g}(x, y), \tag{6}$$

where $\bar{g}(x, y) = f(x, y) - f'(x, y)$, is the high frequency image component in the original image $f(x, y)$ and $f'(x, y)$ is the blurred version, low frequency components, of the $f(x, y)$ and $g(x, y)$ is obtained by Eq. (7).

$$\begin{aligned} g(x, y) &= f(x, y) + [4f(x, y) - f(x-1, y) \\ &\quad - f(x+1, y) - f(x, y-1) - f(x, y+1)] \\ g(x, y) &= 5f(x, y) - [f(x-1, y) + f(x+1, y) \\ &\quad + f(x, y-1) + f(x, y+1)]. \end{aligned} \tag{7}$$

$\frac{1}{16} *$

1	2	1
2	4	2
1	2	1

Fig. 2 Weighted average filter mask.

0	-1	0
-1	5	-1
0	-1	0

Fig. 3 Filter for unsharp masking.

The above equation can be represented by the following mask processing as given in Fig. 3. After the channel-2 processing is over, DWT is applied on the image to get the channel-2 sub-bands. Locations with nonzero coefficients that are not previously registered as location of strong edges are taken as location of weak edges and registered in the location table of same size of the sub-band. The procedure of identification of strong and weak edges corresponding to microcalcifications is also explained in the algorithm given below.

Algorithm of the proposed method:

(1) *Obtain Y_1 (Wavelet transform coefficients after median or average filters is applied to the input image).*
(2) *Obtain Y_2 (Wavelet Transform coefficients after Unsharp marking is applied to the input image).*
(3) *Obtain Y_3 (Wavelet Transform coefficients from the input image directly).*
(4) *Obtain the location of strong edges from Y_1.*

$$if\ CH_{y_1}(i, j) \neq 0;\ then\ ch(i, j) = 1.$$

where $CH_{y_1}(i, j)$ is directional sub-band of size $N \times N$, ch(i,j) is the location table of same size.
(5) *Obtain the location of weak edge in the sub-band from Y_2 if $CH_{y_2}(i, j) \neq 0$ and the same point in the location table, $ch(i, j) = 0$, then mark the location as 2, i.e. $ch(i, j) = 2$.*
(6) *Using Y_3 and location table, if $ch(i, j) = 1$ then $CH_{y_3}(i, j)$ is taken as location of strong edge. Else, if $ch(i, j) = 2$ then $CH_{y_3}(i, j)$ is taken as the location of weak edge.*
(7) *Steps (4–6) are repeated for all sub-bands used.*
(8) *Mapping of coefficients according to the strong and weak edge locations using Eq. (9).*
(9) *Reconstruction of images using modified coefficients.*

The location of strong and weak edges are labeled in the location table as shown in Eq. (8).

$$w_j^i(n_1, n_2) = \begin{cases} 1 & \text{for strong edge} \\ 2 & \text{for weak edge} \end{cases}. \tag{8}$$

The coefficient of the every sub-band image corresponding to the location of the table is mapped as detailed below in Eq. (9).

$$\hat{y}_j^i(n_1, n_2) = \begin{cases} y_j^i(n_1, n_2), & \text{if } \mathrm{e}_j^i(n_1, n_2) \le T_j^i \\ g_j^i y_j^i(n_1, n_2), & \text{if } \mathrm{e}_j^i(n_1, n_2) > T_j^i \end{cases}. \quad (9)$$

where n_1 and n_2 denote coordinates in the spatial domain for jth sub-band in ith scale or level, e_j^i is the energy at the location with reference to the neighborhood corresponding to y_j^i, and g^i and T_j^i are the local gain and threshold at level i, respectively. T_j^i is proportional to the standard deviation of pixel values in each y_j^i, that are as given in Eqs. (10) and (11).

$$T_j^i = \frac{1}{2}\sqrt{\frac{1}{N^2}\sum_{n_1=1}^{N}\sum_{n_2=1}^{N}(y_j^i(n_1, n_2) - m_y)^2}, \quad (10)$$

where m_y is the mean value of y_j^i and $N \times N$ is the size of the sub-image.

$$g_j^i = \frac{T_j^{i_{\max}}}{T_j^i}, \quad (11)$$

where $T_j^{i_{\max}} = \max\{T_j^i, 1 \le i \le L\}$ for $j = 1, \ldots, M$.

Performance Measures

The improvement in images after enhancement is difficult to measure. A processed image is said to be enhanced over the original image if it allows the observer to better perceive the desirable information in the imaging. In images, the improved perception is difficult to quantify. There is no universal measure, which can specify both the objective and subjective validity of the enhancement method. In practice, many definitions of the contrast measure are used. Here, three parameters are used to measure the enhancement level of the image that are used in the literature. They are namely, Measure of Enhancement (EME), Absolute Mean Brightness Error (AMBE), and Discrete Entropy (H).[17,18] The quantitative measure of these three parameters is tabulated in Table 1. When the value of EME is too high, it indicates over enhancement in the output image and it leads to loss of local information, fine details, due to washed-out output image. On the other hand, a very low value of EME hides the local information due to under enhancement. A standard reference method for over or excessive enhancement is histogram equalization technique (HE). For justification and validation of quality of image enhancement, one more additional parameter is used which is called AMBE. It is defined as the absolute difference between the input and output mean of the image. The expression for AMBE may be given as shown in Eq. (12).

$$\mathrm{AMBE} = |E(x) - E(y)|, \quad (12)$$

where, $E(x)$ is the mean of the input image, $E(y)$ is the mean of the output image. Lower value of AMBE implies better brightness preservation. The least value of AMBE indicates the closeness of output image to the original image. The least value of AMBE is justified by referring

Table 1. Quantitative Measures EME, AMBE and H (H and EME of Input Images are Included in the First Column).

Mammogram Images	EME				AMBE				H			
	HE	CLAHE	HM-LCE	DWT-EE	HE	CLAHE	HM-LCE	DWT-EE	HE	CLAHE	HM-LCE	DWT-EE
mdb 209 (5.06-164.98)	188. 39	179.82	178.47	166.89	102.8	21.19	16.07	0.03	3.83	5.52	5.43	5.05
mdb 211 (4.43-136.55)	187.43	165.59	161.35	135.32	112.52	6.98	4.81	0.09	3.13	5.20	4.08	4.04
b 212 (4.35-124.20)	187.01	161.90	157.86	120.99	114.23	8.01	6.34	0.03	3.25	5.20	4.87	4.37
mdb 213 (3.79-92.88)	187.69	160.51	147.94	92.77	135.70	12.42	8.16	0.0008	2.75	4.0068	4.01	3.81
mdb 214 (3.72-90.26)	187.79	160.58	148.06	90.17	139.83	15.23	9.85	0.01	2.65	3.97	3.97	3.73
mdb 218 (5.21-169.05)	180.14	179.43	178.99	168.74	88.85	13.16	13.04	0.02	4.08	5.80	5.85	5.19
mdb 219 (5.47-126.00)	188.45	181.98	180.75	175.98	80.13	10.62	8.50	0.04	9.97	5.70	5.59	5.47
mdb 222 (4.57-126.70)	186.50	162.12	157.65	124.44	111.87	12.70	9.45	0.03	9.47	5.50	5.19	4.57
mdb 223 (3.71-93.38)	187.67	159.87	147.21	92.65	140.33	17.07	9.77	0.02	2.74	4.0026	4.01	3.72
mdb 226 (4.16-116.28)	187.08	158.93	156.85	113.04	126.31	15.99	15.07	0.01	3.11	5.21	4.90	4.17
mdb 227 (3.69-129.75)	188.37	164.43	157.97	126.66	134.44	8.23	5.45	0.0135	2.55	4.22	3.99	3.73

Table 1. (*Continued*)

Mammogram Images	EME				AMBE				H			
	HE	CLAHE	HM-LCE	DWT-EE	HE	CLAHE	HM-LCE	DWT-EE	HE	CLAHE	HM-LCE	DWT-EE
mdb 231 (5.35-169.78)	187.43	180.89	178.71	170.64	86.48	23.15	19.0099	0.17	2.26	5.90	5.76	5.39
mdb 236 (5.18-168.02)	187.11	177.26	177.75	168.79	83.06	5.65	9.24	0.03	4.03	5.79	5.83	5.16
mdb 238 (4.39-141.29)	186.17	160.68	158.19	139.94	116.79	14.23	12.94	0.03	3.35	5.43	5.11	4.46
mdb 239 (5.38-72.47)	187.34	181.04	179.68	173.02	70.51	1.99	4.30	0.0041	4.15	5.90	5.89	5.40
mdb 240 (5.38-169.56)	187.04	180.79	178.77	170.79	69.73	3.28	3.86	0.03	4.09	5.92	5.91	5.38
mdb 241 (3.65-99.70)	187.77	160.93	148.99	101.81	129.75	9.17	5.81	0.04	2.77	4.04	4.01	3.69
mdb 248 (5.12-166.34)	188.19	180.00	179.35	166.52	93.82	16.91	16.65	0.06	3.37	5.74	5.78	5.13
mdb 249 (4.57-135.71)	186.86	165.33	161.61	134.62	106.46	7.85	7.04	0.08	3.36	5.53	5.14	4.59
mdb 252 (4.36-139.34)	186.82	162.35	161.25	134.18	113.68	13.07	12.37	0.04	4.14	5.49	5.86	4.38
mdb 253 (5.25-170.24)	186.89	179.76	178.39	170.77	75.46	6.27	8.71	0.01	4.05	5.87	5.59	5.26
mdb 256 (5.00 -168.12)	188.52	180.40	179.10	168.64	83.33	12.42	12.67	0.0050	4.05	5.67	5.59	5.04
AVG (4.38-135.02)	187.06	170.21	166.13	141.24	105.28	11.62	9.96	0.039	3.96	5.25	5.11	4.62

the AMBE value of unsharp masking technique and highest value is taken from HE. Discrete entropy (H) is the third measure used in this work to evaluate the enhancement performance. Discrete entropy is the statistical measure to determine randomness of the given image which is described as follows in Eq. (13).

$$\text{Entropy}(H) = -\sum P_i \log_2 p_i. \qquad (13)$$

Low value of H of final image indicates less number of edges in the image while high value of H declares more number of edges. The value of H of output image should be slightly greater than that of the input image.

RESULTS

Standard Mammographic Image Analysis Society (MIAS) database mammogram images having microcalcification are used to evaluate image enhancement methods CLAHE, HM-LCE and proposed DWT-EE using the Matlab software. The objective of the work is to give meaningful information of microcalcification. i.e. artifact should be avoided during image enhancement while preserving and emphasizing the edge information present in the image. Otherwise, a false positive diagnosis, normal made into abnormal, will result due to artifact in the image and false negative, abnormal made into normal, will happen due to poor contrast enhancement in the final mammogram image.

Figure 4 shows the subjective enhancement results and visual quality of the recent existing image enhancement methods CLAHE and HM-LCE. The subjective quality of these methods have been improved than the original images. There are significant contrast enhancement in the output image. While comparing the CLAHE with HM-LCE, over enhancement problem is reduced in the second one than in CLAHE. But detection of microcalcification is easily possible after post-processing is done over the output image of these two methods. The result of post-processing is shown in Fig. 5 where column b and c show the results after applying Laplacian filter, post-processing, over the enhanced images produced by CLAHE and HM-LCE methods. The problem of need of post-processing is avoided in case of the proposed DWT-EE method and it is shown in Fig. 6. Figure 6 shows that the proposed method gives the distinguished edge emphasized output image where visibility of microcalcifications is easier than the other two methods even without any post-processing. The small dots are the indications of presence of microcalcifications in the mammogram image in Fig. 6. This is the significant improvement of this edge enhancement method for the efficient detection of microcalcification.

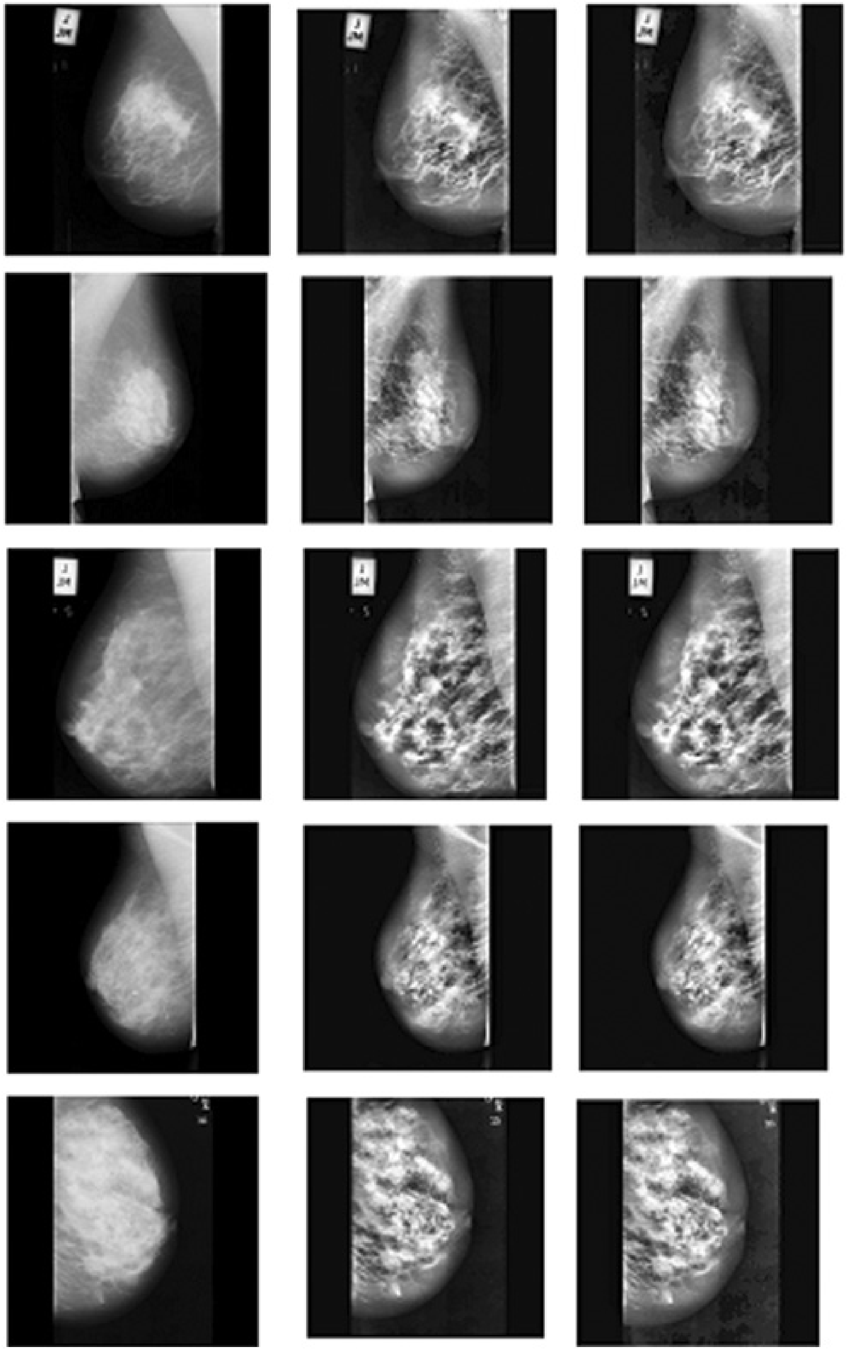
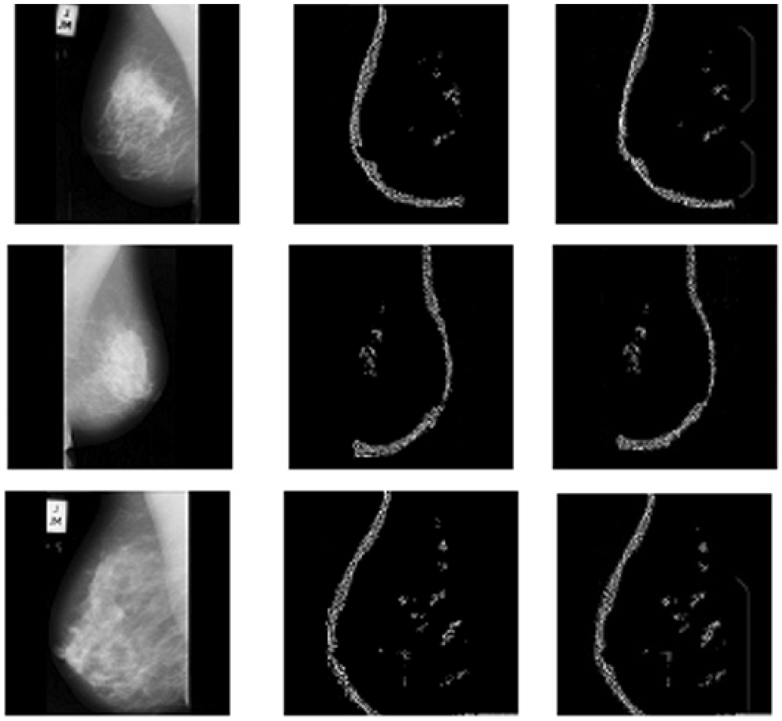


Fig. 4 Enhancement results, Column 1: Input mammogram images from top to bottom (mdb209, mdb212, mdb219, mdb227 and mdb236), Column 2: Results of CLAHE technique, Column 3: Results of HM-LCE.

The method also eliminates the need of feature extraction and classification stages in the detection methodology. It is a very good advantage of this proposed method in the field of digital mammogram analysis. The figure indicates the edge emphasized mammogram images for three levels of wavelet decomposition in its multiresolution investigation. The results of level 1 decomposition keep good representation of microcalcification and level 2 decomposition results are better in representing the microcalcification with slight blurring in the output mammogram image. There is no problem in visualizing the microcalcification due to the blurring effect in the output image of level 2 decomposition. But the next higher level decompositions results are giving more artifacts in the output image so that results of higher level wavelet decompositions will not support for the detection of microcalcification. Among higher level decompositions, the result of level 3



(A) **(B)** **(C)**

Fig. 5 Response of the Laplacian filter for the enhanced images **(A)** Input mammogram images from top to bottom (mdb 209, mdb 212 and mdb 219) **(B)** Results for CLAHE **(C)** Results for HM-LCE.

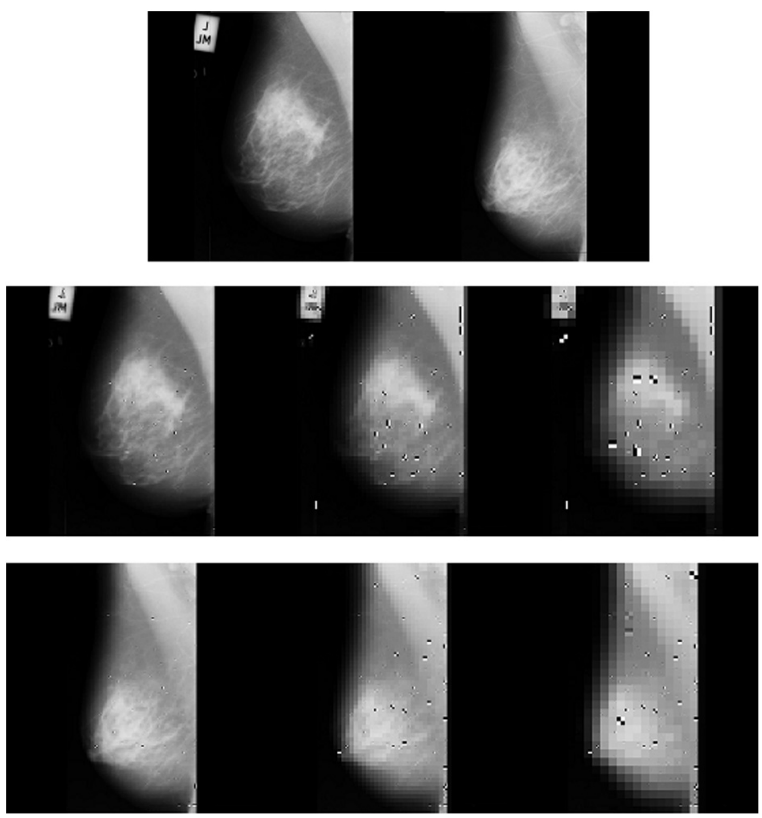
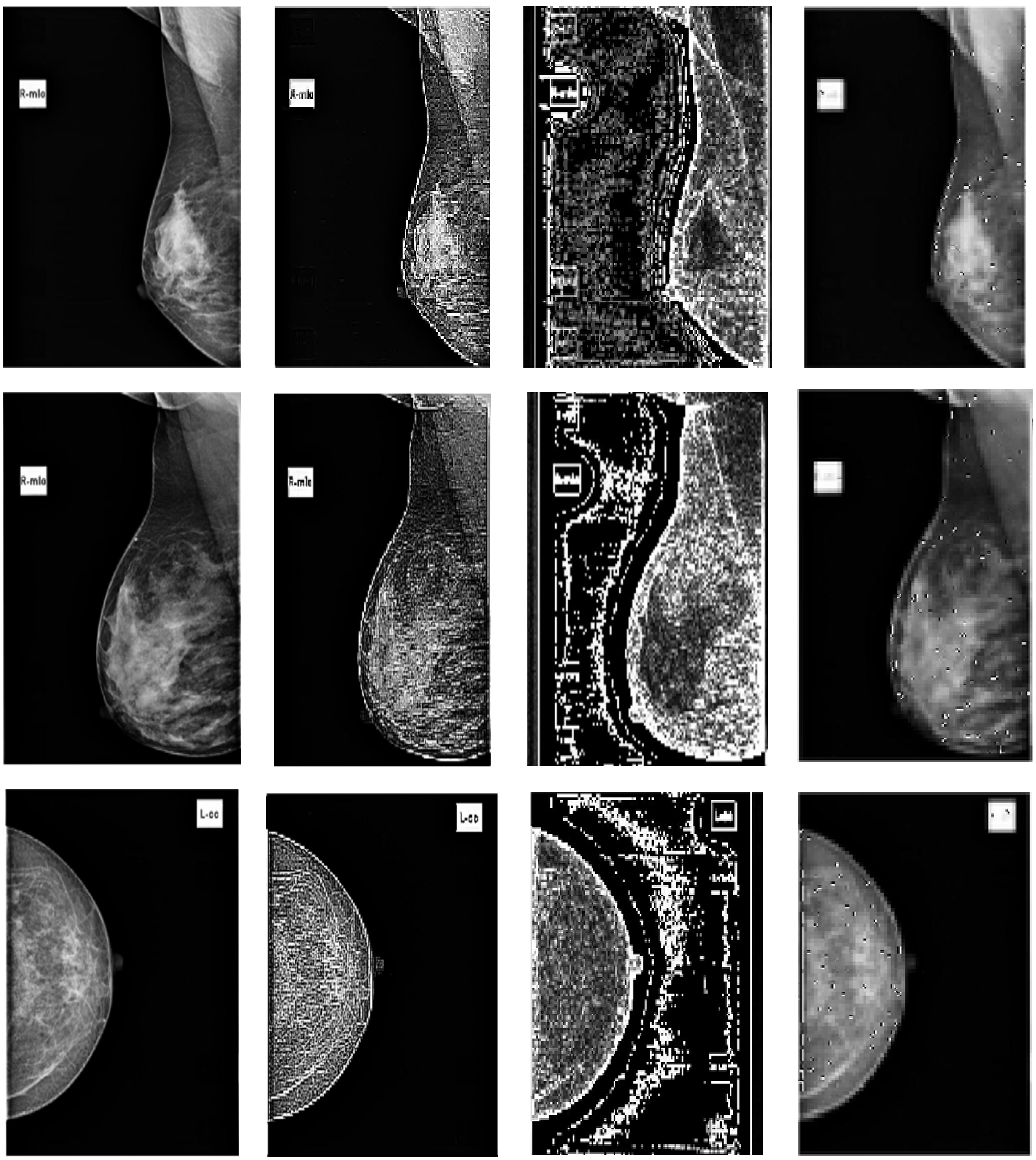


Fig. 6 Results for the proposed DWT-EE method for different decomposition levels Row 1: Original mammograms with microcalcification (mdb 209 and mdb 211) Row 2: Results for Level 1, Level 2 and Level 3 wavelet decomposition for mdb 209 Row 3: Results for Level 1, Level 2 and Level 3 wavelet decomposition for mdb 211.

decomposition is only included in which presence of artifacts are noticed. Because, higher level decompositions (3 and above) contain more dc components than the lower level decompositions (1 and 2), the presence of dc components in the higher level decompositions are the reasons for artifacts produced in the output image. As microcalcifications are related to high frequency components of the image, level 1 and level 2



(A) (B) (C) (D)

Fig. 7 Results of detection of microcalcification by DWT-EE and other edge enhancement method for clinical images **(A)** Input clinical mammograms from top to bottom (adb 01, adb 05, adb 09) **(B)** For Laine method **(C)** For Alonso method **(D)** For proposed DWT-EE.

decompositions are appropriate stages for the representation of microcalcification. This effect of higher level decompositions is true and was also observed in many literatures dealt with mammogram images based on wavelets. These subjective results show the difference between enhancement performance of the methods CLAHE, HM-LCE and DWT based proposed method (DWT-EE). The results of the proposed method are also compared with recent edge enhancement methods to justify the efficiency of the proposed method in the detection process. Figure 7 proves the efficient detection of microcalcification by the proposed method for clinical images with microcalcifications when compared with edge enhancement methods proposed by Alonso[19] and Laine.[20] The figure clearly indicates the artifacts introduced by the methods described by Alonso and Laine

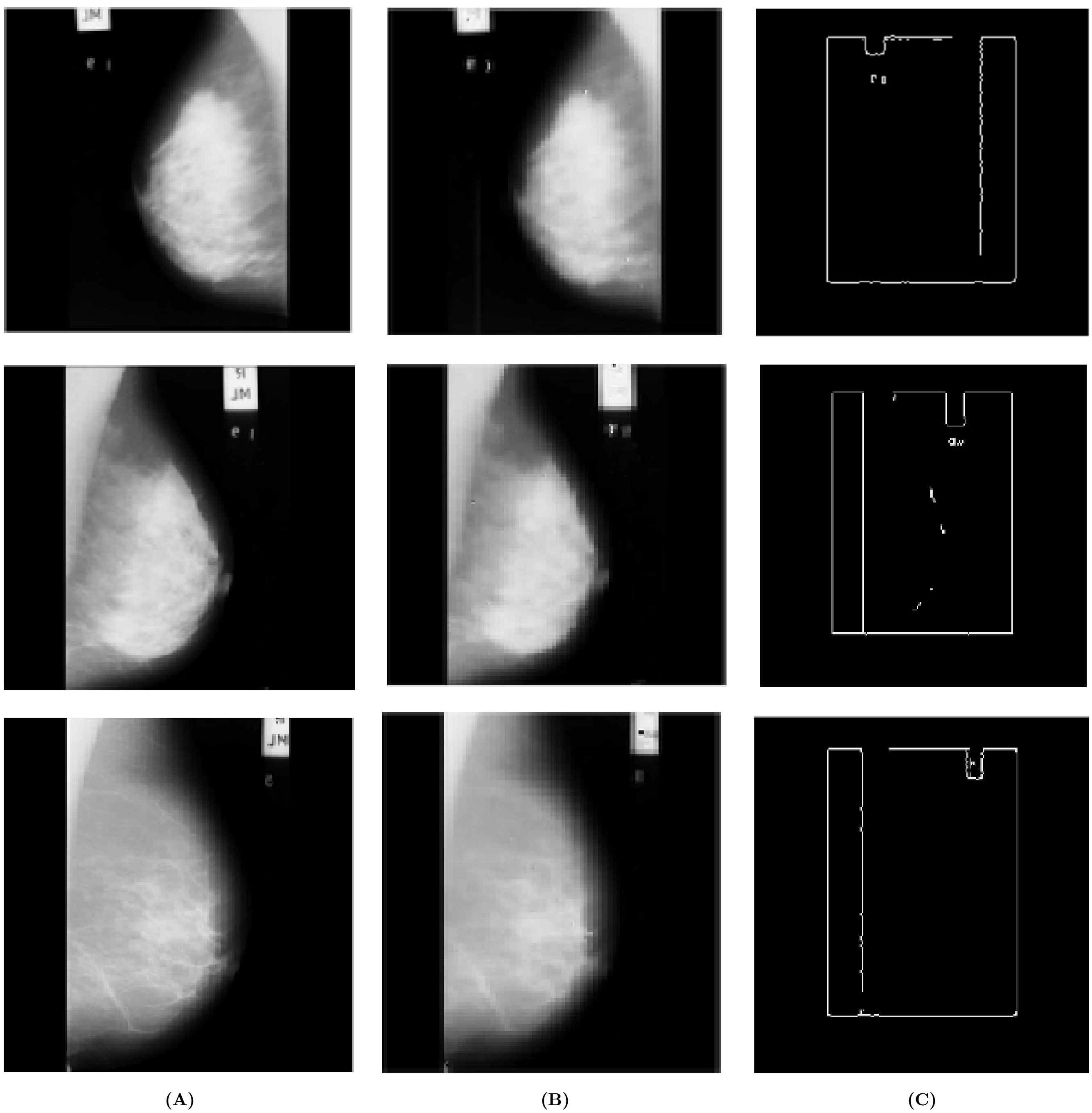


Fig. 8 Results for normal mammograms **(A)** Input mammogram images from top to bottom (mdb003, mdb004, mdb014) **(B)** Results of DWT-EE **(C)** Results of Sobel operator for images in **(B)** (No indication of microcalcification in both images in **(B)** and **(C)**).

and effective detection of microcalcification is visible from the results of the proposed method to the clinical images. The performance of the proposed method for normal images, without microcalcification, is also tested and given in Fig. 8. For normal mammogram images, the proposed method does not give any false indication of microcalcification. Only the boundary of the breast is detected as edge in these images. Figure 9 shows the histogram of the enhanced images for existing methods along with proposed method as an additional measure of performance. On observing the histograms of the images, the proposed DWT-EE exhibits a histogram which is more close to that of the original image that proves the capability of preserving the originality of input images.

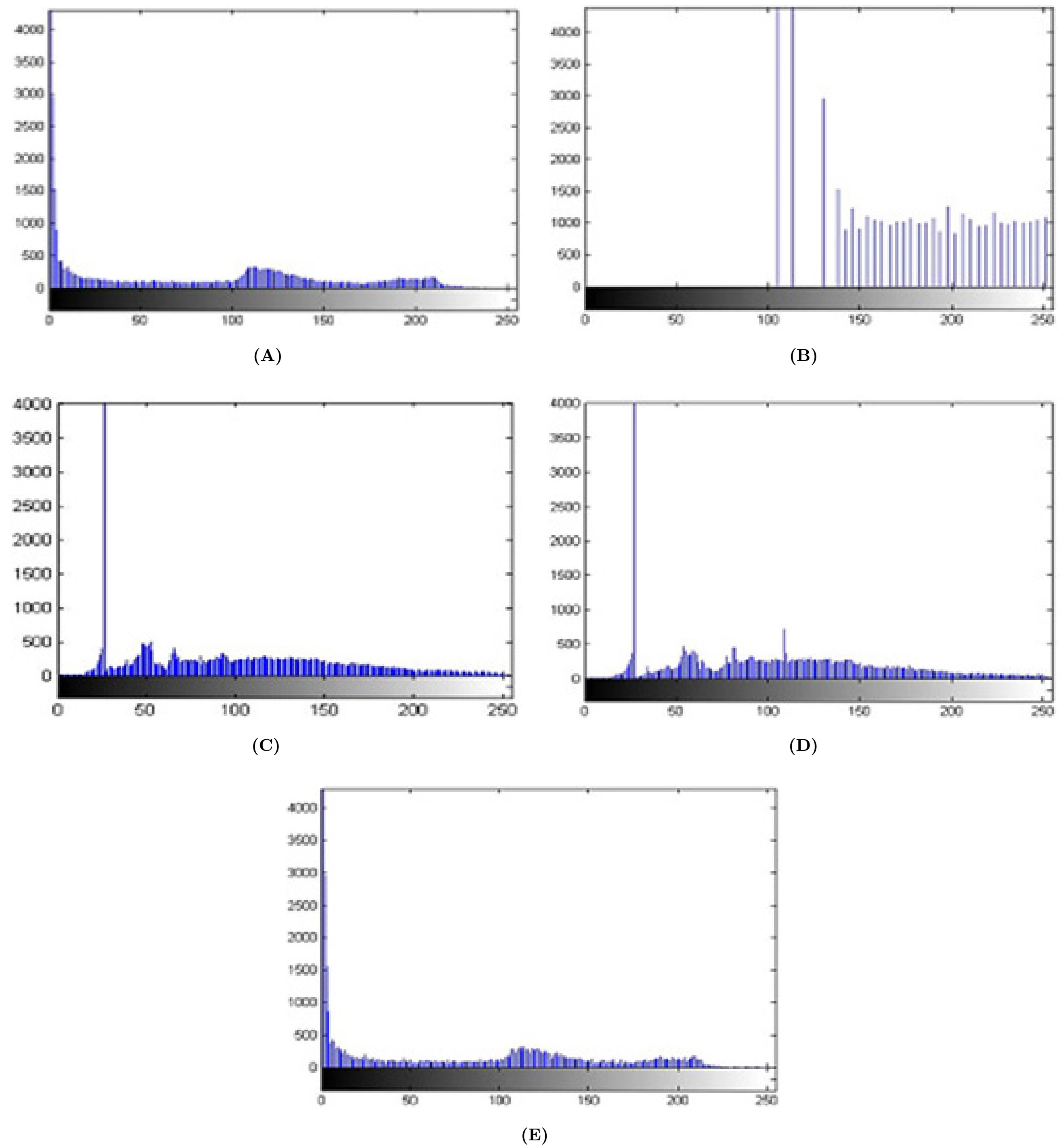


Fig. 9 Histogram of output images for performance evaluation **(A)** for original image **(B)** for HE **(C)** for CLAHE **(D)** for HM-LCE **(E)** for proposed DWT-EE.

DISCUSSION

This section is to discuss the performance of the proposed method and validate its performance in the detection of microcalcification. The performance of the proposed method can also be evaluated by quantitative measures and justified with the discussion made as above by using the parameters mentioned in the "Performance Measures" section. In the case of quantitative investigations as indicated in Table 1, in case of EME and AMBE, value of HE is taken as the highest value for reference, because it offers excessive enhancement in the image which is tested in the work and also accepted by literatures. DWT-EE method provides the lowest EME value which ensures reduction in excessive enhancement while emphasizing the edges or microcalcification. (Average EME values for 22 mammogram images with microcalcification in Mias data base, HE = 187.06, CLAHE = 170.21, HM-LCE = 166.13 and DWT-EE = 141.24).

AMBE of the proposed method is the lowest one in the table which also justifies the edge enhancing performance by the method. (Average AMBE, HE = 105.28, CLAHE = 11.62, HM-LCE = 9.96 and DWT-EE = 0.039). The AMBE values for HE is very high which shows the deviation of its output image from the original image. The least value of AMBE for the proposed method promises to produce artifact free results, i.e. deviations from the original image for the output image is less in case of the proposed method. As the proposed method concentrates on only edges which contribute less area in any image, EME and AMBE values will be very small and it is proved from the quantitative measure as obtained in the Table 1.

Discrete entropy (H) is one of the measures to indicate the information available in the image where HE only gives lowest value due to loss of information by its excessive enhancement. (Average H(4.38), HE = 3.96, CLAHE = 5.25, HM-LCE = 5.11 and DWT-EE = 4.62). The value of H for the final image should be a value nearby to the H value of original image that is appreciable in the entropy analysis. Because it ensures preservation of edges in the original image which indicates that the edge emphasized DWT-EE does not affect the information available in the given input image. It is ensured that the average H of DWT-EE (4.62) is closer to that of the original images (4.38) than that of CLAHE (5.25) and HM-LCE (5.11) methods. It shows that the proposed method only focuses on edges in the original images which does not give much value for H, but a slight increase in the average H value than that of the input images proves the edge emphasizing ability of the method. From Table 1 it is also proved that performance of DWT-EE is tested for all mammogram images with microcalcification in Mias database and it does not require any post-processing. Tables 2 and 3 bear values of the quantitative measures for different wavelet decomposition levels. The EME and AMBE values are increasing for higher levels of decomposition which indicates excessive enhancement or artifact in the output image while H values are decreasing for the above case which stands reduction in information for the output image for higher level of decomposition due to reduction in randomness in the stage. On weighing all these parameters, the lowest level of decompositions are suitable for the detection of microcalcification which is also ensured in the subjective quality analysis where first and second level decompositions give better results. Figure 10 shows the graphical representation for variation of quantitative measures for different wavelet decomposition levels. From this representation, it is justified that higher level decompositions are not contributing for the detection of microcalcification. The curve of H takes a decreasing path for higher level decompositions which shows that artifacts are produced for these level of decompositions and the artifacts are not

Table 2. Quantitative Measures (H, EME, AMBE) for Different Decomposition Levels in the Proposed DWT-EE Method to mdb209 and mdb212 (MIAS database images).

Image Performance Measure	MDB209			MDB212		
	H	EME	AMBE	H	EME	AMBE
L1	5.0612	164.937	0.0285	4.3521	131.079	0.0073
L2	5.0594	165.721	0.0285	4.352	130.096	0.0073
L3	5.0666	167.494	0.0285	4.3249	127.031	0.0073
L4	5.0457	173.531	0.0286	4.3418	125.022	0.0073
L5	5.0041	178.747	0.0286	4.3009	134.557	0.0073
L6	4.3794	189.924	0.0289	3.4591	148.879	0.0072
L7	3.0385	217.115	0.0293	2.3192	165.612	0.007
L8	2.3685	230.132	0.0304	1.5659	195.307	0.0066
L9	1.8791	243.568	0.0332	1.1836	228.605	0.0051

Table 3. Quantitative Measures (H, EME, AMBE) for Different Decomposition Levels in the Proposed DWT-EE Method to mdb222 and mdb238 (MIAS database images).

Image Performance Measure	MDB222			MDB238		
	H	EME	AMBE	H	EME	AMBE
L1	4.5734	137.252	0.0071	4.392	139.56	0.0064
L2	4.5728	136.839	0.0071	4.391	139.086	0.0064
L3	4.5629	138.436	0.0071	4.4147	135.781	0.0064
L4	4.5809	140.682	0.0071	4.4604	131.749	0.0064
L5	4.5000	145.193	0.0071	4.5213	143.887	0.0063
L6	3.5338	158.893	0.0073	3.9982	157.001	0.006
L7	2.4792	173.971	0.0079	2.7009	173.933	0.0047
L8	1.5981	203.198	0.0100	2.7009	173.933	0.0047
L9	1.1888	235.881	0.0130	1.2367	233.854	0.0079

considered by the parameter. Similarly, the values of parameters EME and AMBE start increasing for higher level decomposition which indicates the parameters are responding to average components unlike parameter H. The absence of average components in the low level decomposition is ensured so that the values are almost constant in that levels and presence of microcalcifications that belong to high frequency region is proved in that low level decompositions. Thus, the role of these parameters in evaluating the edge enhancement is justified and proved.

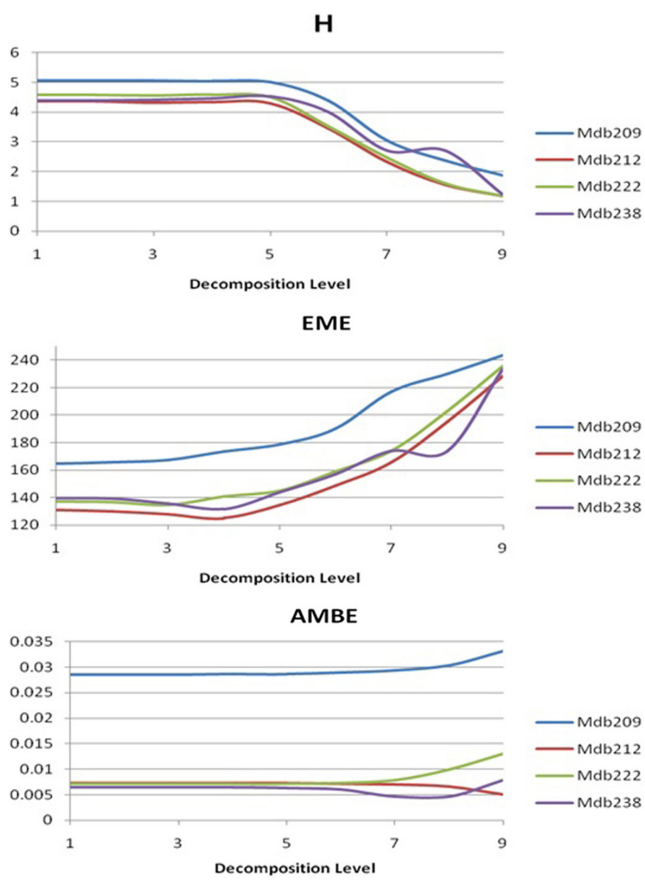


Fig. 10 Variation of performance measures EME, AMBE and H for different decomposition levels.

CONCLUSION

The proposed DWT-EE method provides an efficient detection of microcalcifications of input mammogram images. Edge components and microcalcification, available in the mammogram image are separated into weak and strong edges according to the frequency domain analysis and the localization of microcalcification in the image is highly ensured. Based on the energy of the wavelet coefficients, the mapping of the coefficients is done to emphasize the edges. It ensures the closeness of the resultant image to the input image. It also provides less artifact free image enhancement while testing for normal mammograms. This new approach helps to detect fine details of microcalcifications from the resultant mammogram image itself. The experimental results of data obtained are encouraging in subjective and objective measures for Mias database mammogram images and clinical mammograms. Without any post-processing like Laplacian, Sobel operator or otsu applied to the output image, the detection of microcalcification is highly ensured by the method. For further extension, the reliability of detection of microcalcification at various levels of noise environment should be investigated for more number of clinical mammograms.

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