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ORIGINAL PAPER

A Wavelet-Based Mammographic Image Denoising and Enhancement with Homomorphic Filtering

Pelin Gorgel · Ahmet Sertbas · Osman N. Ucan

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Abstract Breast cancer continues to be a significant public health problem in the world. The diagnosing mammography method is the most effective technology for early detection of the breast cancer. However, in some cases, it is difficult for radiologists to detect the typical diagnostic signs, such as masses and microcalcifications on the mammograms. This paper describes a new method for mammographic image enhancement and denoising based on wavelet transform and homomorphic filtering. The mammograms are acquired from the Faculty of Medicine of the University of Akdeniz and the University of Istanbul in Turkey. Firstly wavelet transform of the mammograms is obtained and the approximation coefficients are filtered by homomorphic filter. Then the detail coefficients of the wavelet associated with noise and edges are modeled by Gaussian and Laplacian variables, respectively. The considered coefficients are compressed and enhanced using these variables with a shrinkage function. Finally using a proposed adaptive thresholding the fine details of the mammograms are retained and the noise is suppressed. The preliminary results of our work indicate that this method provides much more visibility for the suspicious regions.

P. Gorgel (✉) · A. Sertbas
Computer Engineering Department, Engineering Faculty,
Istanbul University,
34320Avcilar,
Istanbul, Turkey
e-mail: paras@istanbul.edu.tr

O. N. Ucan
Electrical and Electronics Engineering Department,
Engineering Faculty, Istanbul University,
34320Avcilar,
Istanbul, Turkey

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Introduction

In recent years, breast cancer has caused a significant number of deaths in woman population and constituted more than 30% of cancer incidences in both developing and developed countries [1]. In order to detect breast cancer at early stages, mammography is the best radiographic method available today. Mammography is indispensable for women older than 40 years as the risk of breast cancer is increased. However it is not always perfect and adequate because of the fuzzy nature of the mammograms and the low contrast between the breast cancer and its surroundings. Detection of small malignancies is especially difficult in younger women who tend to present denser breast tissue. On the other hand, lesions like calcifications have high attenuation properties and low local contrast, but are small in size. So, the visibility of small tumors, and any associated microcalcifications, is a problem in the mammography technology based on analog film. Therefore many research centers are developing several new technologies to detect breast tumors including digital mammography, where computers assist in the interpretation of the X-rays. The critical and essential contrast enhancement process can be improved using digital mammography [2, 3]. Several approaches have been proposed for enhancement in the literature. In the approach of Wirth et al. [4], the enhancement of digital mammograms was based on morphological enhancement. The difference between the original image and its grayscale opening were performed by means of non-flat structural elements. In order to improve the contrast of the microcalcifications, the breast region was isolated and morphological pre-processing was used to suppress the background artifacts. Using deterministic fractal approach, Huai Li et al. [5] improved enhancement by modelling the mammographic patterns. The background noise was measured by the standard derivation. Removal was performed by subtracting a low pass filtered version of the image from itself. Lena et al. [6] proposed an enhancement system using local non-linear modification of multiscale gradient magnitudes provided by the wavelet transform. Denoising was accomplished by adaptive soft-thresholding and contrast enhancement by a local non-linear gain operator. In the study of Elsherif and Elsayad [7], a non-linear enhancement function based on the soft-thresholding scheme was applied to the images decomposed by the wavelet transform. The enhancement transformation was cumulative and monotonically increasing which preserved the order of intensity information. After the wavelet packet coefficients were soft thresholded, the coefficients were filtered with sharpening filter. The technique was applied especially to the irregular breast masses. Papadopoulos et al. [8] tested five image enhancement algorithms introducing the contrast limited adaptive histogram equalization, the local range modification, the discrete wavelet linear stretching and shrinkage algorithms. They achieved the highest performance in two mammographic datasets, for the local range modification and the wavelet-based linear stretching methodology. In Dominguez and Nandi's [9] enhancement routine, statistical measures of the pixel intensities in local neighborhoods were employed to automatically set the parameters of the transform applied to each pixel. In order to obtain effective enhancement over all mammographic structures of different sizes, the enhancement routine was wrapped into a multi-scale processing framework. The objective of the procedure in [9] was to increase the contrast between mammogram structures and their background, while providing a relatively uniform intensity to all of the structures.

The main problem of the approaches mentioned above is the need of the noise estimation, which may be difficult to obtain in some situations, especially for images having inherent noise. One of the faults encountered when using these approaches [4–9] is that they invariably enhance the noise while trying to improve the contrast and sharpening the edges or eliminate the fine details while trying to denoise.

Scharcanski and Jung [10] described a new method for mammographic image enhancement based on the wavelet transform. At each resolution, coefficients associated with noise and coefficients associated with edges were modelled by Gaussian and Laplacian random variables respectively, and a shrinkage function was assembled based on posterior probabilities. The shrinkage functions at consecutive scales were combined, and then applied to the wavelets coefficients. The purpose was eliminating the noise while enhancing the fine details in the mammograms. But their technique is inadequate to perform this task. Because denoising is not an alternative of enhancement. When the experimental results are analyzed it can be seen that the noise is partly suppressed and the enhancement of the edge details is not implemented efficiently. Therefore in this paper, we advance the Scharcanski and Jung's [10] approach to perform the contrast enhancement by combining their denoising method with homomorphic filtering and the proposed adaptive thresholding. In our method, the decomposed approximation coefficients are passed through a homomorphic filter. This filter provides an efficient enhancement that emphasizes the suspicious regions with low contrast. Next, while the detail coefficients are considered to be distributed according to the Gaussian probability density function (pdf), the edge and fine data are considered to be distributed according to the Laplacian pdf. A shrinkage function is constituted based on Bayesian posterior probability using the remodelled detail coefficients. Finally an adaptive thresholding function is applied to these coefficients after the inverse wavelet transform so the remainder noise resembling very small points is eliminated. Thus the image is pre-processed to improve its local contrast and the discrimination of subtle details. On the other hand Scharcanski and Jung [10] use a poor global thresholding that can not perform a sufficient result to suppress the noise in small edge details and the approach has a limited effect on high density tissues. The explanatory flow chart of our study is demonstrated in Fig. 1. The experiments demonstrate that the proposed method can effectively enhance the contours and fine details of the mammographic features which will be useful for breast cancer diagnosis.

The rest of the paper is organized as follows. The "Discrete wavelet transform" section gives a description of the wavelet transform. The "Proposed denoising and enhancement method" section describes the proposed method. The "Experimental results" section presents the experimental results and finally the "Conclusions" section gives our conclusions.

Discrete wavelet transform

To compute the wavelet transform with two detail images [10], a smoothing function $\varphi(x, y)$ and two wavelets $\psi^i(x, y)$ are needed. The dilation of these functions are denoted by:

$$\phi_t(x,y) = \frac{1}{t^2}\phi\left(\frac{x}{t},\frac{y}{t}\right), \psi_t^i(x,y) = \frac{1}{t^2}\psi^i\left(\frac{x}{t},\frac{y}{t}\right), \quad i = 1,2, \qquad (1)$$

t demonstrates the scale and equals to 2^j.

The dyadic wavelet transform $f(x, y)$ at the t scale has two detail components, given by:

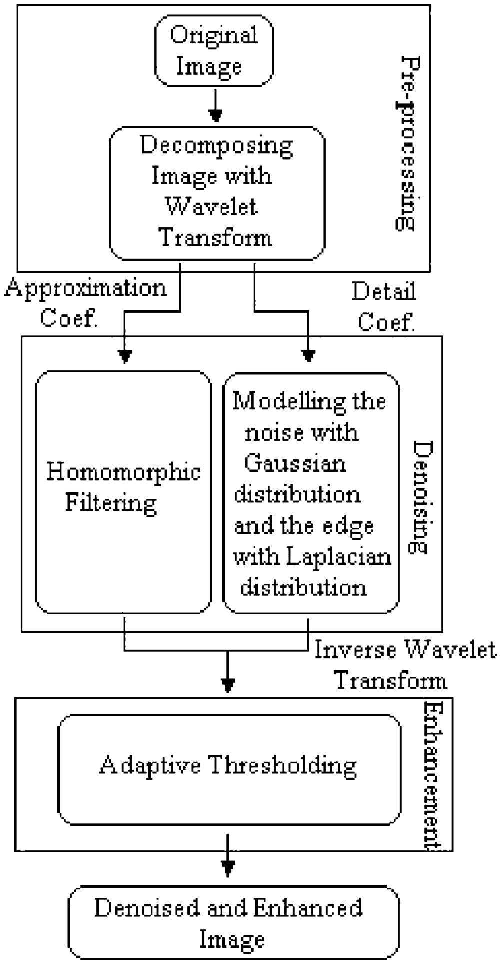


Fig. 1 Flow chart of the proposed method

$$W^i_{2^j} f(x,y) = \left(f \times \psi^i_{2^j}\right)(x,y), i = 1,2, \tag{2}$$

and one low-pass component, given by:

$$T_{2^j} f(x,y) = (f \times \phi_{2^j})(x,y) \tag{3}$$

The details in the x and y directions are represented by the coefficients $W^1_{2^j} f(x,y)$ and $W^2_{2^j} f(x,y)$ respectively. In this way the image gradient at the resolution 2^j can be approximated by:

$$W_{2^j} f(x,y) = \begin{pmatrix} W^1_{2^j}\ f\ (x,y) \\ W^2_{2^j}\ f\ (x,y) \end{pmatrix}. \tag{4}$$

In this work, the discrete wavelet transform (DWT) is used since we are dealing with the digital images $f[n, m]$. The basic idea of the DWT is approximating a signal through a set of basic mathematical functions. In DWT the signal's multi-resolution decomposition is implemented into four subbands called the approximation (low frequency component) and details (high frequency component). The approximation A indicates a low resolution of the original image. The detail coefficients are horizontal (H), vertical (V) and diagonal (D). This decomposition is repeated to further increase the frequency resolution. The approximation coefficients are decomposed with high and low pass filters and then down-sampled [11]. This is represented as a binary tree with nodes pointing a sub-space with different time–frequency localization. The tree is known as a filter bank as seen in Fig. 2.

Proposed denoising and enhancement method

After the wavelet transformation of a given digital image $f[n, m]$, we obtain a decomposed detail coefficient group consists of one level horizontal detail $W^H_{2^1} f[n,m]$, one level vertical detail $W^V_{2^1} f[n,m]$, one level diagonal detail $W^D_{2^1} f[n,m]$, two level horizontal detail $W^H_{2^2} f[n,m]$, two level vertical detail $W^V_{2^2} f[n,m]$ and finally two level diagonal detail $W^D_{2^2} f[n,m]$. We propose the first step of enhancement by applying the homomorphic filter to the approximations while shrinking the details based on posteriori probabilities to discriminate coefficients associated with edges from coefficients associated with noise. The adjusted approximation and details are adaptively thresholded so the objects can be separated from the background and suspicious areas can be identified much more easily. Finally we compute the inverse wavelet transform to obtain the processed image.

Homomorphic filtering

A good deal of control over the illumination and reflectance components is able to be gained with a homomorphic filter. This control requires specification of a filter function $H(u, v)$ that affects the low and high frequency components of the Fourier transform in different ways. An image $f(x, y)$ can be expressed as the product of illumination and reflectance components [12]:

$$f(x,y) = i(x,y)r(x,y) \tag{5}$$

and we define:

$$z(x,y) = \ln f(x,y) = \ln i(x,y) + \ln r(x,y), \tag{6}$$

$$Z(u,v) = F_i(u,v) + F_r(u,v), \tag{7}$$

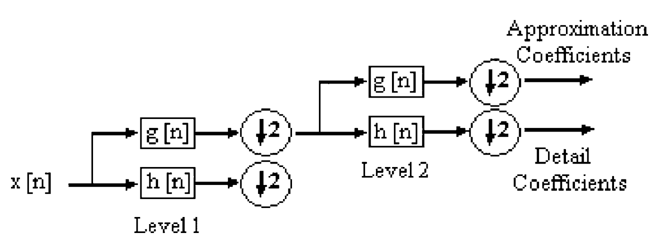


Fig. 2 Wavelet decomposition tree

$Z(u, v)$, $F_i(u, v)$, and $F_r(u, v)$ demonstrates the Fourier transforms of $z(x, y)$.

If is processed by means of a filter function $H(u, v)$, is the Fourier transform of the result:

$$S(u,v) = H(u,v)Z(u,v) = H(u,v)F_i(u,v) + H(u,v)F_r(u,v) \tag{8}$$

So $s(x, y)$ is the inverse Fourier transform of and can be expressed in the form:

$$s(x,y) = i'(x,y) + r'(x,y) \tag{9}$$

Finally, our desired enhanced image, denoted by that is:

$$g(x,y) = e^{s(x,y)} = e^{i'(x,y)} \times e^{r'(x,y)} = i_0(x,y)r_0(x,y). \tag{10}$$

In this particular application, the key to the approach is the separation of the illumination and reflectance components achieved in the form shown in Eq. 7. The homomorphic filter function $H(u, v)$ can then operate on these components separately as indicated in Eq. 8. The filter $H(u, v)$ can be shown as:

$$H(u,v) = (\gamma_H - \gamma_L)\left[1 - e^{-c\left(D^2(u,v)/D_0^2\right)}\right] + \gamma_L \tag{11}$$

where D_0 is a specified distance from the origin of the transform, $D(u, v)$ is the distance from point (u, v) to the center of the frequency rectangle, constant c has been introduced to control the sharpness of the slope of the filter function as it transitions between γ_L and γ_H. A brief of the homomorphic filtering process is given in Fig. 3.

Wavelet shrinkage

The wavelet shrinkage is a signal denoising technique based on the idea of adjusting the wavelet coefficients. The aim is to produce signal with lesser amount of noise. A nonlinearity that reduces low amplitude values and retains high amplitude values is implemented. Our detail coefficients $\hat{W}^H_{2^1} f[n,m]$, $\hat{W}^V_{2^1} f[n,m]$, $\hat{W}^D_{2^1} f[n,m]$, $\hat{W}^H_{2^2} f[n,m]$, $\hat{W}^V_{2^2} f[n,m]$ and $\hat{W}^D_{2^2} f[n,m]$ are shrunk according to the Eq. 12 for j=1,2:

$$\begin{aligned} \hat{W}^H_{2^j} f[n,m] &= W^H_{2^j} f[n,m] S^H_{2j}[n,m] \\ \hat{W}^V_{2^j} f[n,m] &= W^V_{2^j} f[n,m] S^V_{2j}[n,m] \\ \hat{W}^D_{2^j} f[n,m] &= W^D_{2^j} f[n,m] S^D_{2j}[n,m] \end{aligned} \tag{12}$$

where $S^i_{2j}[n,m]$ are called shrinkage factors for i=H, V, D. In order to determine a shrinkage function $S(x)$ the distribution coefficients are analyzed. In this work we model the mammographic image noise by an additive zero-mean Gaussian noise [10]. The detail coefficients of an image constituted only by Gaussian noise may be considered Gaussian distributed with standard deviation σ_{noise}. Under these circumstances, the probability density function that models the coefficient distribution is given by:

$$p(x|\text{noise}) = \frac{1}{\sigma_{\text{noise}}\sqrt{2\pi}} e^{-x^2/2\sigma^2_{\text{noise}}} \tag{13}$$

Hence, $p(x|\text{noise})$ represents the distribution coefficients considering that image consists of the noise only. On the other hand, the distribution of the wavelet coefficients for noise-free images is sharply peaked near the origin and has long tail due to image edges. So we model such coefficients with Laplacian probability density function, given by:

$$p(x|\text{edge}) = \frac{1}{2b} e^{\frac{-|x-\mu|}{b}}, \quad b = \frac{1}{N}\sum_{i=1}^{N} |x_i - \mu|. \tag{14}$$

Here, N is the number of independent and identically distributed samples μ is the sample median and b is the maximum likelihood estimator. $p(x|\text{edge})$ represents the distribution of coefficients assuming that only edges and homogeneous regions are present in the image. Consequently we consider modeling the decomposed wavelet coefficients of images containing noisy edges and homogeneous regions affected by noise. The coefficients belonging to the tail of the distribution are likely to be edge related and coefficients close to the origin of the histogram are likely to be related to noise [10]. The origin of the histogram is of course Gaussian shaped. We compute the shrinkage function $S(x)$ by the posterior probability function $p(x|\text{edge})$ using Bayesian theorem as follows:

$$S(x) = \frac{(1-\lambda)p(x|\text{edge})}{(1-\lambda)p(x|\text{edge}) + \lambda p(x|\text{noise})}. \tag{15}$$

Here λ is an unknown parameter of the overall coefficient distribution ($0 \le \lambda \le 1$). In this work, we choose the value of near 1 such as 0.8. Because the image is considered that it may have more fine details than noise.

Adaptive thresholding

The proposed denoising technique described above can be extended to local contrast enhancement which preserves edges and other high frequency parts of the mammographic images. It is a nonlinear enhancement method that areas of low contrast are enhanced more than high contrast areas and sharp edges are not blurred. The key point of the wavelet denoising method is that in the wavelet domain the noise is spread fairly uniformly among all coefficients,

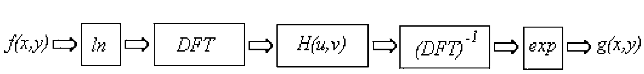


Fig. 3 Homomorphic filtering

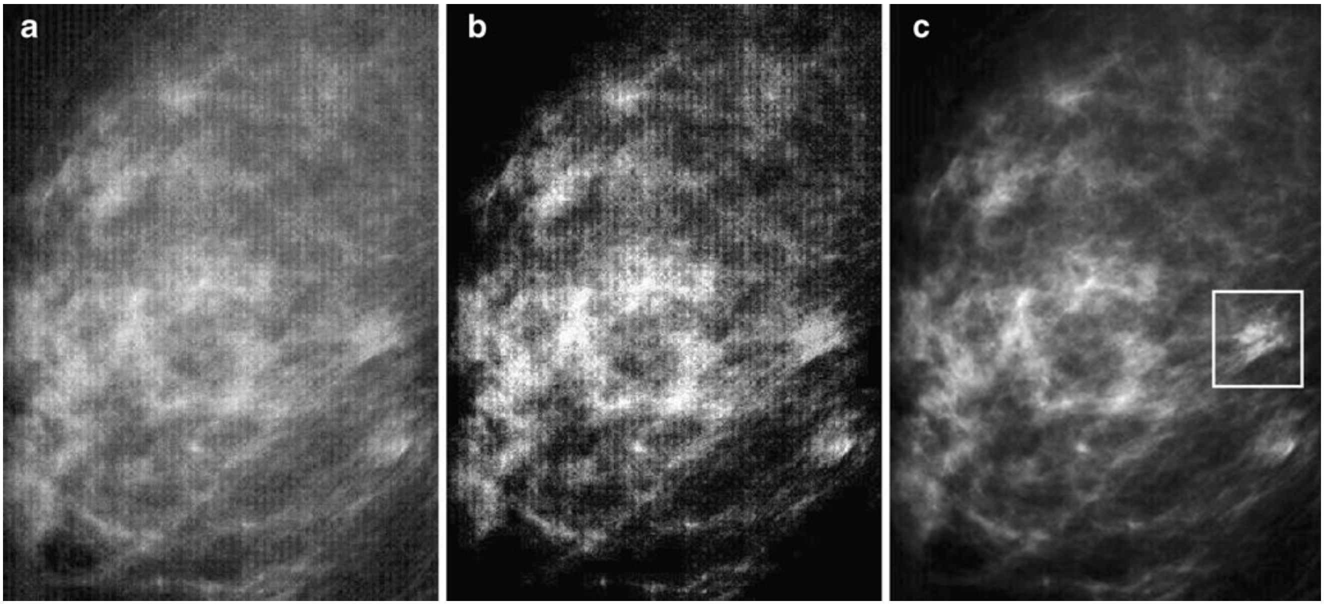


Fig. 4 **a** Original image; **b** enhancement with histogram equalization; **c** image denoised and enhanced using the proposed method

whereas the signal is quite sparse, being concentrated into a small number of coefficients. This is the practical motivation for thresholding of the detail coefficients [13]. We use adaptive local thresholding (LT) which is better for mass detection than global thresholding, because a local threshold value is determined locally for each pixel based on the intensity values of the surrounding pixels [14]. Two variables of the local thresholding should be considered; the window size around the pixel and thresholding value. Local threshold value T is based on a recent denoising result by Birgé and Massart [15], and can be viewed as a variant of the fixed form strategy of the wavelet shrinkage. The local threshold T_{local} applied to the denoised detail coefficients for a given fixed decomposed tree, is defined by:

$$T_{\mathrm{local}} = |c(t^*)|$$

with

$$t^* = \underset{t=1,\ldots,n}{\operatorname{argmin}} \left[-\mathrm{sum}\{c^2(k), k < t\} + 2vt\left(\alpha + \log\left(\frac{n}{t}\right)\right); \right], \tag{16}$$

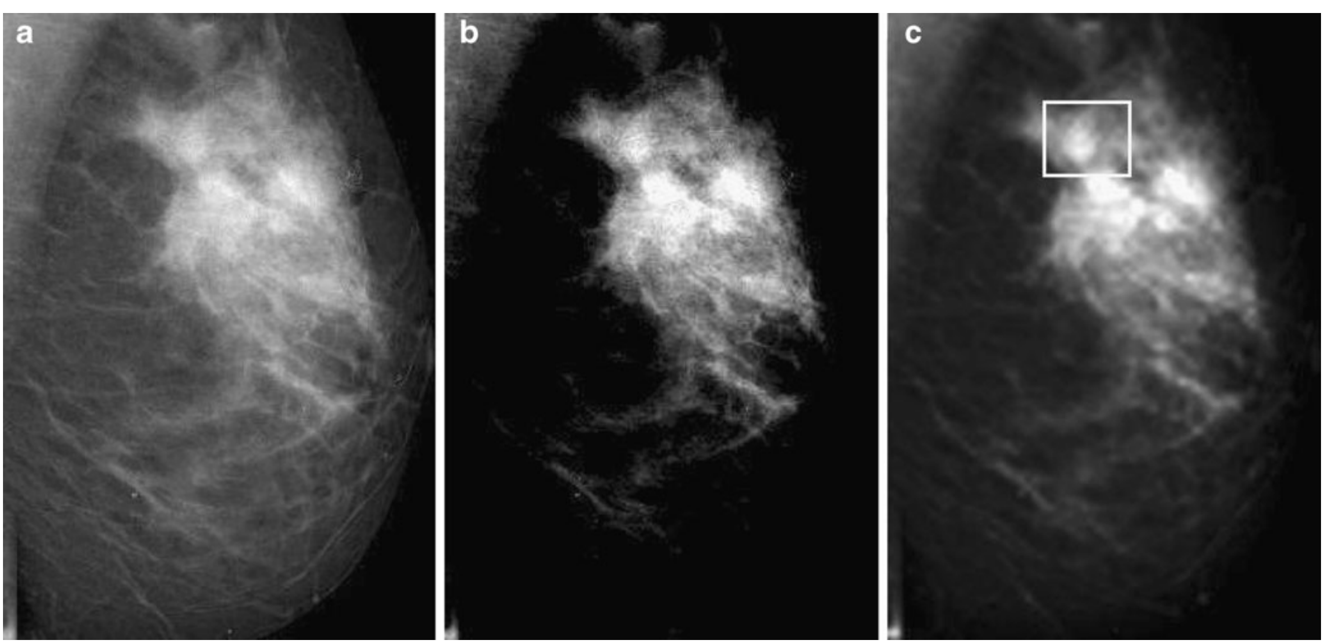


Fig. 5 **a** Original image; **b** enhancement with histogram equalization; **c** image denoised and enhanced using the proposed method

where the sparsity parameter, α is chosen 1.5 for this work. The coefficients are sorted in decreasing order of their absolute value v, the noise variance.

In order to define an enhancement function, first we calculate the local mean m_{local} and the local standard deviation σ_{local} for 5×5 pixel matrix neighbourhood. Then t standard deviation is determined regarding to the coefficient x being larger or smaller than the local mean. It is necessary to specify that if x is small, very small, large or very large. To achieve that, our starting point is dividing the 256 gray levels into 20 sequential parts. The number of levels is demonstrated by k (k=1,2,3,…,20). We find the number k_1 of the suitable gray level interval which the smallest x larger than m_{local} and satisfying equation $x=\sqrt{\sigma_{\mathrm{local}}^2+m_{\mathrm{local}}^2}$. In the same way the number k_2 is found for largest x which is smaller than m_{local} and satisfying the equation $x=\sqrt{m_{\mathrm{local}}^2-\sigma_{\mathrm{local}}^2}$. Afterwards the number of tolerance level k_{tol} is determined. The information about how large or small of the x coefficient compared to the values in its neighborhood is related to whether x is larger than $(k_1+k_{\mathrm{tol}})^{\mathrm{th}}$ or smaller than $(k_2-k_{\mathrm{tol}})^{\mathrm{th}}$ level interval. The mentioned proposed enhancement function which applies the threshold T_{local} with a neighborhood of 5×5 pixel matrix is given by the following rule:

$$E_{2^j}^{\mathrm{detail}}=\begin{cases} x=x-T_{\mathrm{local}}, \left(\text{if} x\geq m_{\mathrm{local}} \text{ and } \sigma_x\geq\sigma_{\mathrm{local}} \text{ and } x\geq \mathrm{array}_{(k_1+k_{\mathrm{tol}})^{\mathrm{th}}}[\mathrm{first}]\right) \\ x=x+T_{\mathrm{local}}, \begin{pmatrix} \text{if } \mathrm{x}\geq \mathrm{m}_{\mathrm{local}} \text{ and } \sigma_{\mathrm{x}}\geq\sigma_{\mathrm{local}} \text{ and } \mathrm{x}< \mathrm{array}_{(\mathrm{k}_1+\mathrm{k}_{\mathrm{tol}})^{\mathrm{th}}}[\mathrm{first}] \text{ or} \\ \text{if } x\geq m_{\mathrm{local}} \text{ and } \sigma_x<\sigma_{\mathrm{local}} \text{ or} \\ \text{if } x< m_{\mathrm{local}} \text{ and } \sigma_x<\sigma_{\mathrm{local}} \text{ and } x\geq \mathrm{array}_{(k_2-k_{\mathrm{tol}})^{\mathrm{th}}}[\mathrm{first}]. \end{pmatrix} \\ x, \qquad \begin{pmatrix} \text{if } x< m_{\mathrm{local}} \text{ and } \sigma_x<\sigma_{\mathrm{local}} \text{ and } x< \mathrm{array}_{(k_2-k_{\mathrm{tol}})^{\mathrm{th}}}[\mathrm{first}] \text{ or} \\ \text{if } x< m_{\mathrm{local}} \text{ and } \sigma_x\geq\sigma_{\mathrm{local}} \end{pmatrix} \end{cases} \tag{17}$$

Here, $\mathrm{array}_{k^{\mathrm{th}}}$ is the set of values in k^{th} gray level and $\mathrm{array}_{k^{\mathrm{th}}}[\mathrm{first}]$ the first element of this array. σ_x is equal to $\sqrt{x^2-m_{\mathrm{local}}^2}$ for $x\geq m_{\mathrm{local}}$ and $\sqrt{m_{\mathrm{local}}^2-x^2}$ for $x<m_{\mathrm{local}}$. This enhancement rule is used to update the denoised wavelet coefficients for detail=H,V,D and j=1,2 and finally, the inverse wavelet transform is applied to obtain the denoised–enhanced image.

Experimental results

The proposed method has been implemented in MATLAB and the approach has been tested on the mammograms acquired from the Department of Radiodiagnostic of the Faculty of Medicine in the University of Akdeniz, and the Faculty of Medicine in the University of Istanbul on which

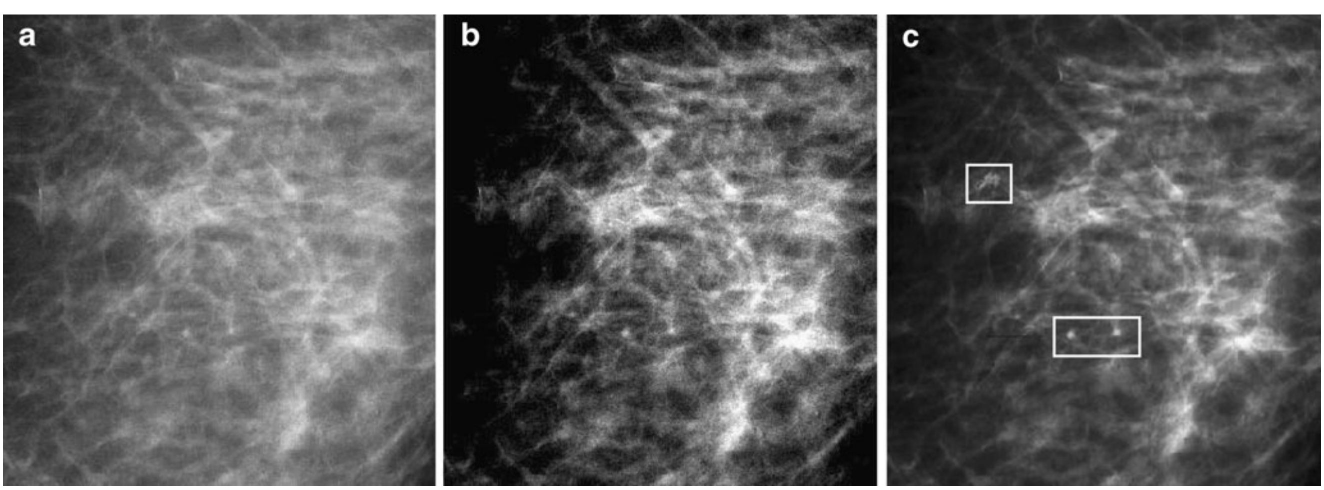


Fig. 6 **a** Original image; **b** enhancement with histogram equalization; **c** image denoised and enhanced using the proposed method

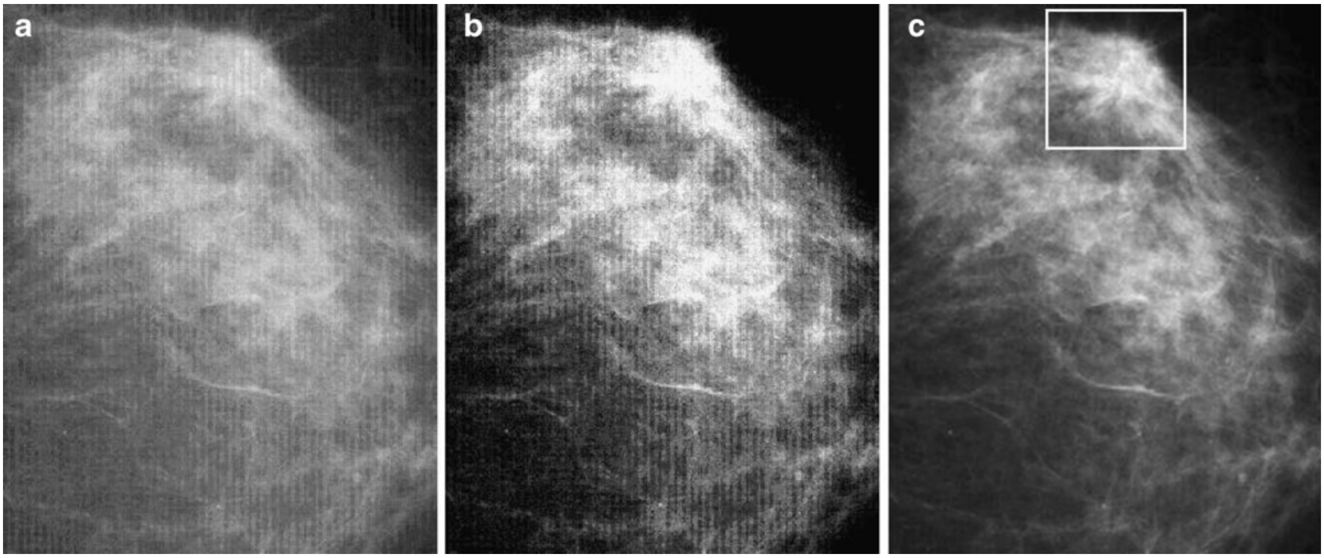


Fig. 7 **a** Original image; **b** enhancement with histogram equalization; **c** image denoised and enhanced using the proposed method

masses were previously marked by experienced radiologists. The used imaging device is a special system named "IMS Giotto Image Full Field Digital Mammography System". Each digital mammogram has the size of 85 µm and 2,560×4,096 pixel matrix. The modulation transfer value and the quantum efficiency is 5 lp/mm and the spatial resolution is 6 lp/mm. There are 55 mammograms in the database taken from 20 different patients.

The implemented method consists of two main steps. Firstly, the original image normalized to grayscale range ([0,255]) is denoised using an approach based on a "bior3.7" wavelet transformation. A homomorphic filter is applied to the approximation coefficients by using Eq. 11 for γ_H=2 and γ_L=1.5. On the other hand the noise in the detail coefficients is assumed to distribute according as Gaussian and the edge data is as Laplacian distribution. The fine detail probability function is calculated using the Bayesian posterior probability depending on Eq. 15 for λ=0.8. This step provides noise reduction as a preprocess of denoising and enhancement system. We propose a local adaptive thresholding enhancement method that behaves according to the information of how large or small the coefficient gray scale numbers are. After the implemented denoising-enhancement method is applied to the mammogram in Fig. 4a, the brightness of the malign tumor gets larger while it gets smaller for the tissue around it as seen in Fig. 4c, so distinguishing the mass from the background is not as difficult as in the original image. There is a low contrast malign mass at the top of the mammogram in Fig. 5a owing to the dense breast and as it can be noticed, this mass is not sharp enough to diagnose. However as demonstrated in Fig. 5c after image denoising

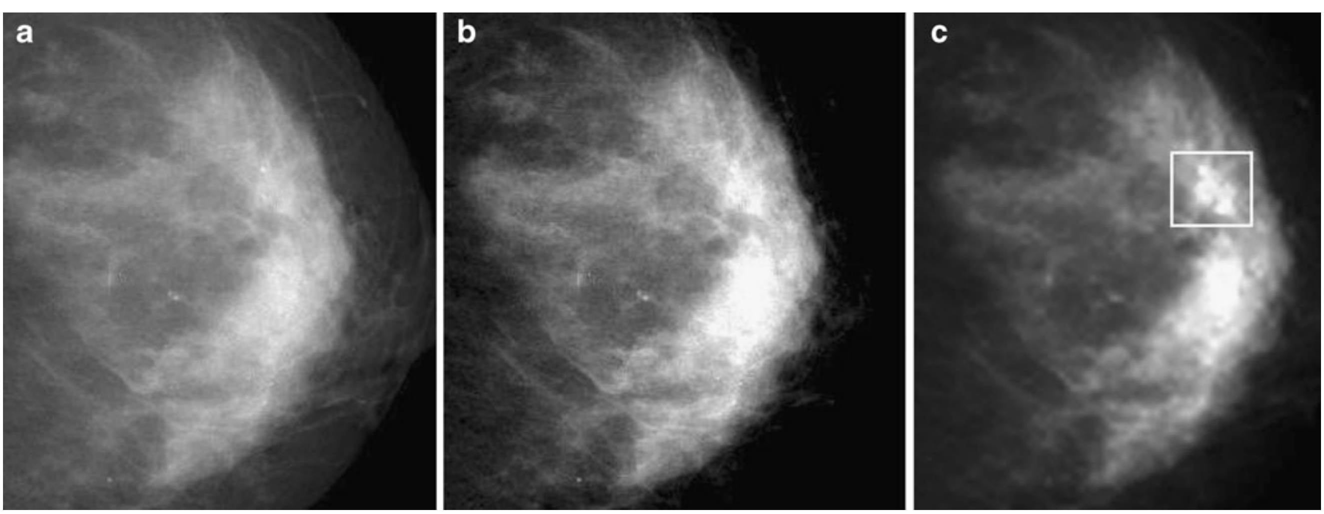


Fig. 8 **a** Original image; **b** enhancement with histogram equalization; **c** image denoised and enhanced using the proposed method

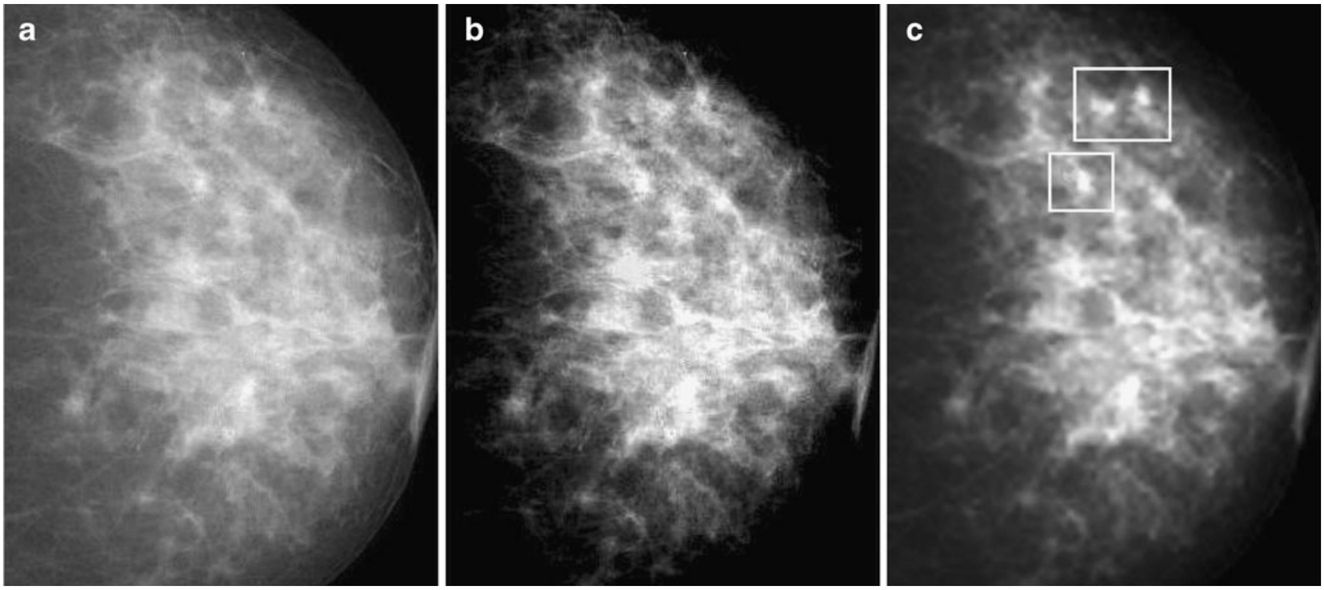
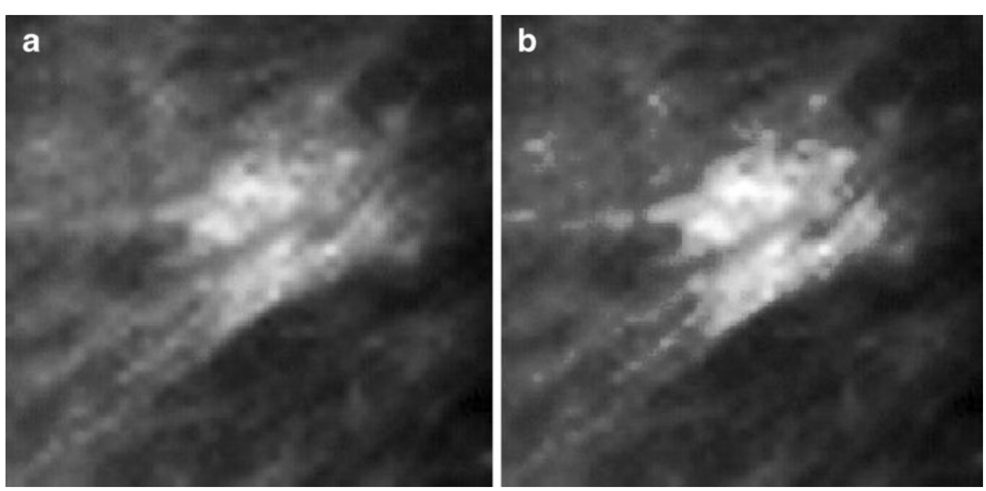


Fig. 9 **a** Original image; **b** enhancement with histogram equalization; **c** image denoised and enhanced using the proposed method

and enhancement, the local contrast has been increased successfully so the malign mass can be clearly outlined in a first visual evolution. Also after the denoising and enhancement of Fig. 6a which represents a mammogram with a few malign lesions, the result is illustrated in Fig. 6c. In the original mammogram the mass at the top is not able to be detected with a naked eye because it is hidden in the blurry breast tissue. In the Fig. 6c, one can notice the mass boundary inside the frame more clearly than in the original image. Also the other lesions which seem like microcalcifications, get brighter after the process. The mammogram in Fig. 7a presents a mass appears to be a bulge. As seen in Fig. 7c the irregular bottom border of the tumor can be detected easier. As we know, it is essential in diagnosis to decide whether the boundary is regular or irregular. Besides the contrast of the tissue surrounding the mass is enhanced. In Fig. 8c similar enhancement results are observed. Although the mass in the original image in Fig. 8a has a very poor contrast, it gets sharpened successfully to guide the radiologist's visual evolution accurately. Figure 9a shows a mammogram presenting two suspicious circular nodules at the top with indistinct borders and a mass under them. In Fig. 9c we can see the result of the proposed method that the brightness of the masses is much more increased than the brightness of the surrounding tissue in order to enhance the visibility. Unlikely, in the region of interest in Fig. 10a the result achieved before adaptive thresholding is given. When it is compared to Fig. 10b one can realize that with the thresholding process the edge and fine detail are enhanced and the regions which have low contrast are sharpened.

Next we compare the results of the proposed method with histogram equalization (HE) which is one of the well

Fig. 10 **a** The denoised image using the proposed method without adaptive thresholding; **b** image denoised and enhanced using the proposed method



known enhancement techniques commonly used for medical images. HE is a common enhancement method used to improve the intensity contrast in medical images. Given an input image, it stretches the dynamic range of the image by virtue of the image's cumulative distribution function, thereby improving the image contrast [16–18]. HE is also used as a comparing enhancement method against the methods based on wavelet shrinkage [10, 19, 20]. Besides there are recently published studies in which the new techniques are developed based on HE [21, 22]. However as seen in Figs. 4b, 5b, 6b, 7b, 8b and 9b, histogram equalization is inadequate for the local contrast and has a limited effect on high density tissues. Therefore to distinguish the nodules from the background and outline the shapes and the boundaries seem more difficult. The experimental results demonstrate that the proposed method produces more efficient results than HE for diagnosing. As mentioned in the "Introduction" section early detection and treatment of breast cancer are the most significant methods to reduce mortality. The preliminary experimental results indicate that our method can help improving the local contrast, making morphological details of the masses more evident in order to success early detection.

Conclusions

In the images belonging to the mammography technology some important image features indicating malignant lesions might be lost or significantly attenuated, especially if the malignant region is located inside an almost homogeneous high intensity image region with very poor contrast. For assistance in early detection of breast cancer we have developed a denoising and enhancement method that improves the transparency of high density tissues, keeping enough contrast to characterize adequately the fine details and the morphology of masses. To demonstrate the effectiveness of the proposed system, we have compared the results with the histogram equalization enhancement technique which causes losing small details and invisibility by over brightening and increasing the contrast of the tissue around the mass. According to the comparative work, it is seen that we provide better results with the proposed method in which low contrast features are more enhanced than the high contrast areas without blurring fine image details such as edges. On the other hand, histogram equalization resulted in losing small details and invisibility by over brightening and increasing the contrast of the tissue around the mass. As a conclusion, the proposed method could better assist mammography specialists to implement computer aided diagnosis of breast cancer.

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