

Contrast Enhancement of Mammographic Images Using Wavelet Transform

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Abstract—Mammography is the most effective method for the early diagnosis and treatment of breast Cancer diseases. However, data sets collected by image sensors are generally contaminated by noise. This ensures the need for image enhancement to aid interpretation. This paper introduces an efficient enhancement algorithm of digital mammograms based on wavelet analysis and modified mathematical morphology. In this proposed method, we adopt wavelet-based level dependent thresholding algorithm and modified mathematical morphology algorithm to increase the contrast in mammograms to ease extraction of suspicious regions known as regions of interest (ROIs). Experimental results show that the proposed algorithm gives significantly superior image quality and better Contrast Improvement Index (CII). Here, to prove the efficiency of this method, we have compared this with various well-known algorithms like VisuShrink and NormalShrink.

Keywords- Mammograms, Modified Mathematical Morphology, Wavelets, Denoising.

I. INTRODUCTION

Breast cancer is the leading cause of death among women, especially in developed and under developed countries. The *National Cancer Institute* estimates that one out of eight women in the United States will develop breast cancer at some point during her lifetime [1]. Primary prevention seems impossible because the causes of this disease still remain unknown. Early diagnosis and treatment is the key to improving breast cancer prognosis. Data sets collected by image sensors are broadly contaminated by noise. Imperfect instruments, problems with the data acquisition process, and interfering natural phenomena can all degrade the data of interest. Furthermore, noise can be introduced by transmission errors and compression.

Mammographic images contain low signal to noise ratio (low contrast) and its fuzzy nature, low differentiability from the surroundings; it becomes too difficult for highly radiologist to analyze mammogram. To deal with above stated problems, it is very important to suppress the noise, to enhance the contrast between the region of interest (ROI) and background. A digital mammogram is created when a conventional mammogram is digitized, through the use of a specific mammogram digitizer or a camera, so it can be processed by the computer. Image enhancement techniques have been widely used in the field of radiology, where the subjective quality of images is important for human interpretation and diagnosis. Many algorithms for accomplishing enhancement have been developed and

applied to medical images such as histogram modification, unsharpmasking, median filters, Gaussian filters, and morphological filters [2, 3]. More recently multiscale techniques have sparked the interest of researchers for contrast enhancement of images, especially wavelet transform. In the wavelet domain, each noisy wavelet coefficient is modified according to a certain threshold - denoising - estimated correctly to obtain good performance of the algorithm. Due to its effectiveness and simplicity, soft thresholding is frequently used in the literature [4]. Alternative approaches can be found in [4, 5], VisuShrink [6] and NormalShrink [7, 8]. Here, we use Modified Mathematical Morphology, Top-Hat, and denoising-wavelet based-level dependent thresholding upon the details of the image to remove noise for contrast enhancement. Then, we compare the enhancement algorithm with VisuShrink, and NormalShrink techniques. Experimental results show that the enhancement algorithm yields significantly superior image quality and higher CII values. The rest of the paper is organized as follows. Section II, describes the enhancement algorithms. Section III discusses some quantitative measurement and experimental results that used for the evaluation of the results. Finally, some conclusions are given in section IV.

II. ENHANCEMENT

Mammographic images are often characterized by low contrast and relatively high noise Content. Enhancement can be accomplished by enhancing contrast, suppressing background, removing noise, and enhancing edges. However, these techniques will also destroy areas of the image where the intensity of the pixels is outside the range of intensities being enhanced. Therefore, we have proposed modified Mathematical morphology to reduce destroys areas of the image.

Two methods for contrast enhancement are discussed in the next section. The first of them is based on modified Mathematical morphology and the second one is based on wavelet analysis. More explanation about each algorithm is given in the following subsections.

A. Modified Mathematical Morphology

Morphological filters are nonlinear signal transformations that locally modify the geometric features of signals. The force of the Mathematical morphology approach comes from the fact that a large class of filters can be represented as the combination of two simple operations: 1) *erosion* and 2) *dilation*. Let Z denote the set of integers and

$X(m, n)$ is a discrete image signal whose domain set is given by $\{m, n \in N1 \times N2\}$, where $N1, N2 \in \mathbb{Z}$. A structuring element S is a subset in \mathbb{Z}^2 with a simple geometrical shape. The erosion and dilation can be expressed as

$$(X \otimes S)(m, n) = \min \{ \alpha \times (1 + I_f) + \min \{ X(m+i, n+j) - S(i, j) \} \} \quad (1)$$

$$(X \oplus S)(m, n) = \max \{ \alpha \times (1 - I_f) + \max \{ X(m-i, n-j) + S(i, j) \} \} \quad (2)$$

$$I_f = \max \{ X(m+i, n+j) - S(i, j) \} - \text{mean} \{ X(m+i, n+j) - S(i, j) \}$$

with $[(m+i, n+j)] \in X, (i, j) \in S$

Where I_f is intensifying factor for intensifying intensity of pixel values. In this paper, we optimize the parameter as method described in [9]. The optimal parameter value is, $\alpha = 1.6375$. On the other hand, the opening and closing are defined as

$$X \circ S = (X \otimes S) \oplus S \quad (3)$$

$$X \bullet S = (X \oplus S) \otimes S \quad (4)$$

Given an image, the opening operation removes the objects having sizes that are smaller than the structuring element. Thus, with a specified structuring element, one can extract different image contexts by taking the difference between the original image and the one processed by the opening operator and the other processed by the closing operator, which is a process called tophat operation. The algorithm is implemented by dual morphological tophat operations followed by a subtraction that is described as follows.

$$TH = X - X \circ S \quad (5)$$

$$BH = X \bullet S - X \quad (6)$$

The top-hat by opening yields an image that contains all the residual features removed by the opening. Adding these residual features to the original image has the effect of accentuating high-intensity structures. The dual residual obtained by using the top-hat by closing, is then subtracted from the resulting image to accentuate low-intensity structures:

$$C = X + TH - BH \quad (7)$$

This reduces high frequencies in image (i.e. noise). However, a drawback of the mathematical morphology technique is that a part of the noise still remains [9]. To remove the remaining noise, we use the Wavelet transform.

B. Wavelet Transform

Wavelets were first introduced to medical imaging research in 1991 in a journal paper describing the application of wavelet transforms for noise reduction in MRI images. The wavelet transform is a decomposition of an image onto a family of functions called a wavelet family, in which all of the basic functions (called wavelets) are derived from scaling and translation of a single function that is called the mother wavelet (or analyzing function).

Dyadic wavelet transform [10], or Redundant (over complete) biorthogonal wavelet representation, has several advantages compared to orthogonal, critically ample, wavelet representation. The subband images are invariant under translation and do not have aliasing. Smooth symmetrical or antisymmetrical wavelet functions can be used [11], allowing alleviation of boundary effects via mirror extension of the signal. Due to these advantages, such representations have been extensively used in image denoising and enhancement applications. Wavelet coefficient represents the “degree of correlation” (or similarity) between the image and the mother wavelet at a particular scale and translation. Thus, the set of all wavelet coefficients gives the wavelet domain representation of the image. After decomposition of the image, the details coefficients can be thresholded. Then, the inverse wavelet transform is performed. This reverse process is called wavelet reconstruction. Since a part of the noise still remains in the image, therefore we want to recover the image from noisy data (i.e. denoising).

C. Denoising algorithm

Image denoising [13] is the processing of images to increase their usefulness and recovery from their noisy data and can be expressed as:

$$I(m, n) = C(m, n) + \sigma e(m, n) \quad (8)$$

Where $I(m, n)$ is the noisy image, σ is Gaussian white noise with unit variance, $e(m, n)$ is the noise level and supposed to be equal to one, and $C(m, n)$ is the original image. The objective of denoising is to suppress the noise part of the image S and to recover the original image C . Generally, denoising procedure involves three stages; decomposition process, threshold detail coefficients and reconstruction process. The wavelet-based procedure also contents three steps.

a) *Wavelet decomposition:* Select a wavelet filter (orthogonal or biorthogonal) and the number of decomposition levels or scales, l , to compute the fast wavelet transform of the noisy image

b) *Threshold detail coefficients:* Select and apply a threshold value to the detail coefficient for each level from the scales 1 to l , where l is the highest level or scale. This can be accomplished by soft thresholding, which involves first setting to zero the elements whose absolute values are lower than the threshold and then scaling the

nonzero coefficients towards zero. Soft thresholding eliminates the discontinuity that is inherent in hard thresholding. The soft threshold signal is as follows:

$$I(m) = \begin{cases} \text{sign}(m)(|m| - t) & \text{if } |m| > t \\ 0 & \text{otherwise} \end{cases} \quad (9)$$

We use a level dependent threshold t (i.e. it is computed at each level j) by the following equation:

$$t_j = \left(\frac{j}{1+j} \right) \times \log_2 (\max(d_j)) \quad (10)$$

Where $j = 1, 2, \dots, l$ is the level of wavelet decomposition, d_j is the corresponding detail coefficients.

c) *Reconstruction process:* Perform a wavelet reconstruction technique based on the original approximation coefficients at level l and then modifies detailed coefficients for levels from l to 1.

By combining the modified mathematical morphology scheme with the wavelet scheme we can get good results. The steps of the proposed denoising or enhancement algorithm are given as depicted in Figure1:

Modified mathematical morphology

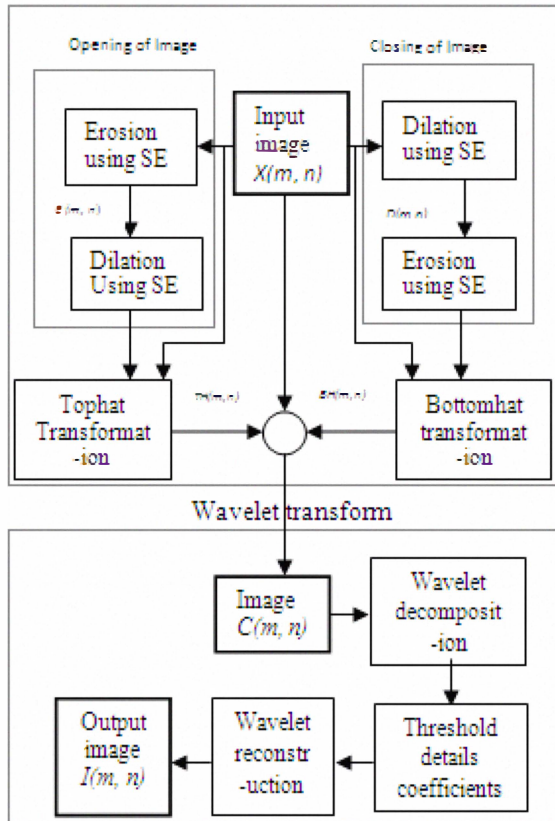


Figure 1. Proposed enhancement algorithm

III. QUANTITATIVE MEASUREMENTS AND EXPERIMENTAL RESULTS

For evaluation of performance analysis of the proposed enhancement algorithm, we used the contrast improvement index (CII) [12] which is defined as follows:

$$C = \frac{C_{Processed}}{C_{Original}} \quad (11)$$

Where, $C_{Processed}$ and $C_{Original}$ are the contrasts for the processed and original images, respectively. The contrast C of an image is defined by the following form

$$C = \frac{f - b}{f + b} \quad (12)$$

Where, f and b denote the mean gray-level value of the foreground and the background, respectively. The local contrast at each pixel is measured within its 5×5 pixel neighbourhood.

The proposed enhancement algorithm, as depicted in figure 1, has been applied on several mammographic images selected from the Digital Databases for Mammographic Image Analysis Society (MIAS) [14]. Here, we used the structuring element S as a disc of radius 5, and biorthogonal wavelets for decomposition and reconstruction, and a threshold t_j computed using (10).

A comparative study has been made on the tested images with two well known VisuShrink and NormalShrink algorithms using CII measure. Table 1 shows a comparative study of our algorithm with VisuShrink and NormalShrink algorithms in terms of CII values.

From the Table 1 and Figure 2 we observe that the introduced enhancement algorithm outperforms the others, and we have enhanced results and a clearer mammogram better than the original one.

TABLE I. CII VALUES OF ENHANCED MAMMOGRAMS AT THE SECOND WAVELET DECOMPOSITION LEVEL.

Images from MIAS Database	Normal shrink	Visushrink	Proposed Method
mbd186	0.98241	0.985582	1.182224
mbd148	0.97916	0.981654	1.207031
mbd147	0.98497	0.986885	1.161082
mbd057	0.97711	0.980593	1.259426

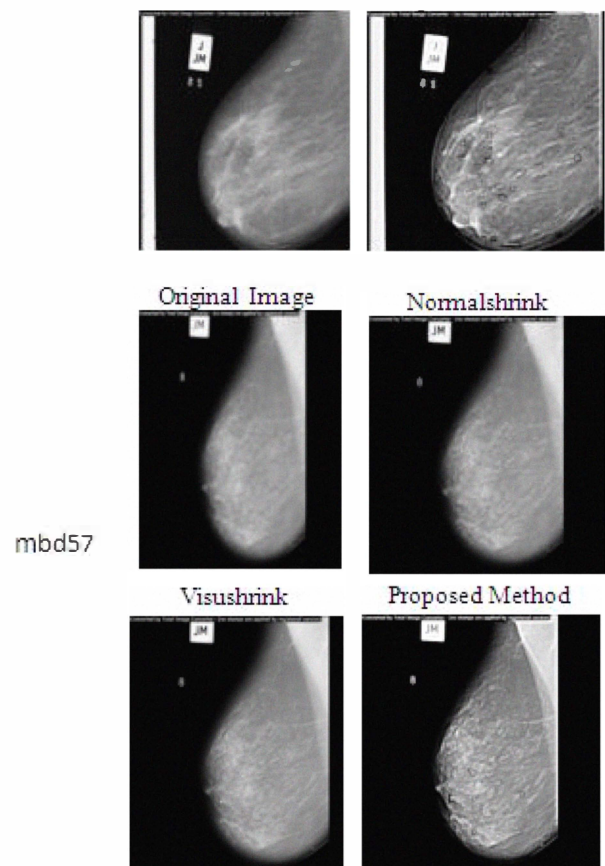
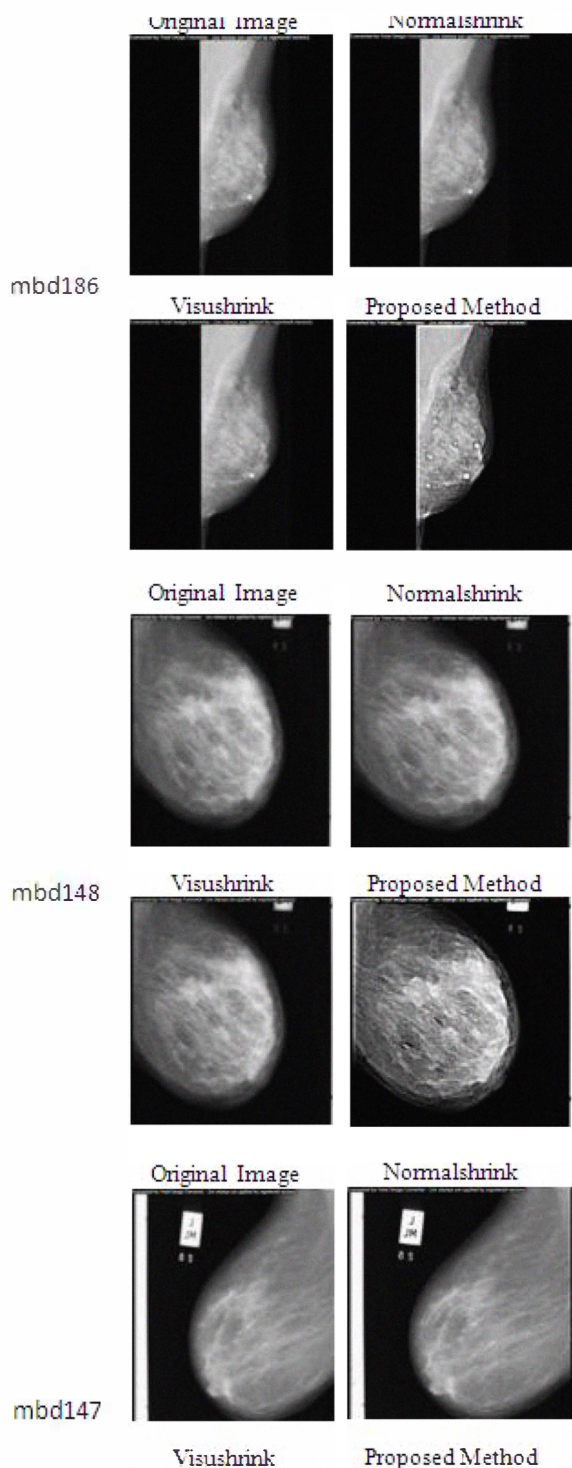


Figure 2. Enhancement results at level 2 of wavelet decomposition for four different Mammograms.

IV. CONCLUSIONS

In this paper an efficient algorithm for detection of breast cancer tumour on digital mammograms images has been introduced. It is based on modified mathematical morphology and wavelet analysis. Morphological Top-hat and Dyadic wavelet-based-level dependent thresholding algorithms have been applied to increase the contrast in digital mammograms images. Experimental results show that the proposed algorithm yields significantly superior image quality and contrast compared to the other well-known algorithms.

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