Feature and contrast enhancement of mammographic image based on multiscale analysis and morphology*

Shibin Wu, Qingsong Zhu, and Yuhan Yang
Key Laboratory for Health Informatics, Shenzhen Institutes of Advanced Technology, Chinese Academy of Sciences, Shenzhen, Guangdong Province, China
{sb.wu, qs.zhu, yh.yang}@siat.ac.cn,

Yaoqin Xie*
Key Laboratory for Health Informatics, Shenzhen Institutes of Advanced Technology, Chinese Academy of Sciences, Shenzhen, Guangdong Province, China
yq.xie@siat.ac.cn

Abstract—A new algorithm for feature and contrast enhancement of mammographic images is proposed in this paper. The approach is based on multiscale transform and mathematical morphology. First of all, the Laplacian Gaussian pyramid transform is applied to decompose the mammography into different multiscale subband sub-images. In addition, the detail or high frequency sub-images are equalized by the contrast limited adaptive histogram equalization (CLAHE) and low frequency sub-images are processed by mathematical morphology. Finally, the enhanced image of feature and contrast is reconstructed from the Laplacian Gaussian pyramid coefficients modified at one or more levels by CLAHE and mathematical morphology. The enhanced image is processed by global non-linear operator in order to obtain natural result. The experimental results show that the presented algorithm is effective for feature and contrast enhancement of mammogram. The performance evaluation of the proposed algorithm is contrast evaluation criterion for image, signal-noise-ratio (SNR) and contrast improvement index (CII).

Index Terms—Laplacian Gaussian pyramid; Multiscale analysis; Morphology; Contrast enhancement; Non-linear operator.

I. INTRODUCTION

Breast cancer has been a significant public health for women in the world and early detection of breast cancer is very essential in the field of medicine before the means to prevent breast cancer have not yet been found. However, there are new cases 234580 and death rate 17.1% from the National Cancer Institute in the United States in 2013 [1]. Breast cancer currently accounts for more than 38% of cancer incidence and a significant percentage of cancer mortality in the developing and developed countries [2].

Thus, it is well known that the early detection and treatment of breast cancer are the most effective key means of reducing mortality. Furthermore, mammography is widely recognized as the only effective and primary imaging modality for the early detection and diagnosis of breast cancer [3-5]. In mammography, low dose x-ray is used for imaging. Hence, the mammographic images are poor in contrast and are contaminated due to the low dose x-ray for imaging. In low-contrast mammograms, it is difficult to interpret between the normal tissue and malignant tissue. Furthermore, it is said that about 10% of all cancerous lesions are missed diagnosis for the poor contrast mammograms [6].

In recent years, there are many researchers proposed all kinds of contrast enhancement algorithms to solve these problems produced by poor contrast images. M. Sundaram et al [6] proposed the histogram based contrast enhancement method to improve the mammography quality, but this method didn’t suppress the amplified noise in histogram equalization progress. Kother Mohideen et al [2] used multiwavelet with hard threshold to denoise and enhance contrast of mammographic images. Harish Kumar et al [7] proposed the algorithm based on morphology and wavelet transform for enhancement of mammographic images. Morrow et al [8] designed a region-based contrast enhancement algorithm for mammograms. Stojic et al [9] developed an algorithm using mathematical morphology to enhance local contrast of mammography. Multiscale analysis technology based on the wavelet transform for mammogram contrast enhancement was applied in [2,7,10-14]. However, wavelet transform leads to undesirable artifacts in the enhanced image [10]. To overcome this shortcoming, we propose a novel approach, in which the multiscale analysis replaces the wavelet transform with the Laplacian pyramid transform. Comparing with the wavelet technique, the Laplacian Gaussian pyramid seems to be a more suitable decomposition method for multiscale analysis [10].

We compare the suitability of these methods for enhancement of mammographic images in general. We propose the approach which seems to be suitable for contrast enhance-
ment of mammograms. The proposed approach decomposes the image by the Laplacian Gaussian and Gaussian pyramid, firstly. Secondly, CLAHE is adopted to enhance contrast of each level sub-image decomposed by Laplacian Gaussian pyramid and Gaussian filter is used to restrain CLAHE to enhance the noise of sub-images. Mathematical morphology is applied to enhance contrast of each low frequency sub-image. Finally, the inverse Laplacian Gaussian pyramid transform is applied to reconstruct the decomposed sub-images to obtain the contrast enhancement image, which is adjusted by non-linear operator.

The rest of this paper is organized as follows. Theory of Laplacian Gaussian pyramid and key features of CLAHE and morphology are detailed in Section II. Section III presents the experimental results and discussion. The conclusion of this paper is stated in Section IV.

II. MATERIALS AND METHODS

A. The Proposed Method

Traditional image enhancement techniques cannot adapt to the varying characteristic of images. The application of a global transform or a fixed operator to an entire image often yields poor results at least in some parts of the given image [17]. In order to solve the problem, we propose a novel approach based on the multiscale analysis and morphology, which can better enhance the local detail information at the same time restrict the modified noise.

To begin with, the original image is decomposed by the Laplacian Gaussian pyramid to obtain low frequency subbands and different scales of the high frequency sub-bands. The morphology can enrich the feature information of low frequency sub-images and enhance the contrast of sub-images in terms of the principle of mathematical morphology. On the other hand, noise in sub-images can be reduced by morphological operations. The low frequency subbands contain the basic information and the overall contrast of image. Therefore, the processing of low frequency data is important and cannot be ignored. For the low pass filtered subband images, we applied the mathematical morphological operations, which combined opening operation with closing operation.

Secondly, Histogram equalization is effective method for image enhancement and used in many literatures for enriching detail information and edges of the whole image. But it will enlarge the noise of image and make the image unnatural visualization at some parts. In additional, the detail information and edges of image belong to the high frequency subbands. Furthermore, high-frequency subbands contain the noise, too. We adapt the CLAHE to enhance the high frequency subbands coefficients, which can not only enhance the contrast of image and enrich the detail information and edges of image, but also effectively suppress the noise.

Finally, we can reconstruct an image, and its size is same as the original image. Using the low frequency coefficients adjusted contrast and the processed high-frequency subbands by the CLAHE to extract the enhanced images due to the Laplacian Gaussian pyramid is of the property of reversal. The global gain operation is adopted to adjust the contrast of reconstructed image in order to make the enhanced image more nature and smoother. The flowchart of the proposed algorithm is shown in Fig. 1.

![Flowchart of the method based on multiscale analysis for enhancement of mammogram.](image)

B. The Laplacian Gaussian Pyramid Transform

The Laplacian Gaussian pyramid was developed by Burt and Adelson in the context of compression of images [10,12]. And the Laplacian Gaussian pyramid has been used to analyze images at multiscale for a broad range of application [12]. The multiscale image contrast enhancement is that the original image is divided into several levels subband images which are enhanced by CLAHE and morphology, respectively. All levels subband images are reconstructed to extract the enhanced image. The flow diagram of the Laplacian Gaussian pyramid for the decomposition and reconstruction processes of image is shown as Fig. 2. The original image is filtered by the Gaussian low-pass and subsampled to produce $g_1$. The image $g_1$ is next interpolated or convolution operation to reproduce the original array size and pixelwise subtracted from the original image to produce $b_0$. This sub-band image $b_0$ is the finest level of the Laplacian Gaussian pyramid. The decimated low-pass image $g_1$ is further Gaussian low-pass filtered and subsampled producing $g_2$, and this is interpolated.
or convolution operation and subtracted from the \( g_1 \), resulting in the second pyramid layer \( b_1 \). All subsequent layers of the Laplacian Gaussian pyramid \( b_k \) are computed by repeating these operations to the subsampled Gaussian low-pass images \( g_k \) from the previous iteration, until the setting pyramid image \( b_{L-1} \) and the last pyramid image \( g_L \) are obtained. The flowchart of the reconstruction process is drawn in the right hand of Fig. 2. The image \( g_L \) is interpolated to the array size of the next finer pyramid level \( b_{L-1} \), and pixelwise is added to this. Interpolation, contrast enhancement and addition are repeated until the reconstructed image at the original resolution level is obtained. The reconstruction is completely reversible if the interpolation filter used in decomposition and reconstruction are identical [10,12-15].

It is obviously that contrast enhancement process is implemented between the \( b_{L-1} \) and \( b_{L-1}' \). The image \( g_L \) is adjusted contrast to obtain contrast enhancement \( g'_L \). And repeating the reconstruction process can extract the enhanced image.

The next morphological operations are the opening and closing, having the same form as their binary counterparts. The opening of image \( I(x,y) \), by structuring elements \( SE \) is defined as erosion followed by dilation and is expressed as equation (3). The closing of image \( I(x,y) \) is defined as dilation followed by erosion and is given by equation (4):

\[
I \circ SE = (I \otimes SE) \oplus SE \quad (3)
\]

\[
I \bullet SE = (I \oplus SE) \otimes SE \quad (4)
\]

Gray-scale opening can remove light details smaller than the structuring element. Similarly gray-scale closing removes dark details smaller than structuring element.

By combining morphological opening and closing various image processing operation can be achieved. There are two morphological operations known as top-hat (\( TH \)) and bottom-hat (\( BH \)) transformation. The top-hat by opening is defined as the difference between the original image and its gray scale opening using structuring element \( SE \) and it is defined as equation (5):

\[
TH = I - (I \circ SE) \quad (5)
\]

Similarly dual bottom-hat by closing is the difference between the gray-scale closing image and original image is described by equation (6):

\[
BH = (I \bullet SE) - I \quad (6)
\]

Based on the theoretical analysis above, the \( TH \) transformation is an effective technique for enhancing small bright details from a background. Conversely, the dark features can be extracted from a brighter background by the \( BH \) transformation. In order to enhance the local contrast of the mammograms, the processing procedure is adding original image to the top-hat transformed image, and subtracting the bottom-hat image. Furthermore, its efficiency in image contrast enhancement has been proved by [9]. The calculate formula is given as follows:

\[
C = I + TH - BH \quad (7)
\]

C. Mathematical Morphology

Mathematical morphology originated in set theory establishes the relationship between the geometry of physical system and some of its property. As such, morphology offers a unified and powerful approach to different image processing problems [15,16]. We apply the morphological Dilation and Erosion operation to process the different sub-band images. It can enhance the contrast of image and enrich the information. On the other hand, it filters the noise of image. A structuring element \( SE \) of rectangle shape is used.

The erosion of a gray-scale digital image \( I(x,y) \) by a structural element \( SE(i,j) \) is defined as follows [7,9,10].

\[
(I \circ SE)(m,n) = \min\{I(m-i, n+j) - SE(i,j)\} \quad (1)
\]

The gray-scale dilation can be described as

\[
(I \oplus SE)(m,n) = \max\{I(m-i, n-j) + SE(i,j)\} \quad (2)
\]

The next morphological operations are the opening and closing, having the same form as their binary counterparts. The opening of image \( I(x,y) \), by structuring elements \( SE \) is defined as erosion followed by dilation and is expressed as equation (3). The closing of image \( I(x,y) \) is defined as dilation followed by erosion and is given by equation (4):

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I \circ SE = (I \otimes SE) \oplus SE \quad (3)
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\[
TH = I - (I \circ SE) \quad (5)
\]

Similarly dual bottom-hat by closing is the difference between the gray-scale closing image and original image is described by equation (6):

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\[
C = I + TH - BH \quad (7)
\]

D. Contrast Limited Adaptive Histogram Equalization

Comparing with the traditional histogram equalization, the AHE has the advantage of good local contrast. But the AHE need to compute the local histogram and accumulate distribution function of every pixel, it is extremely computational intensive. Besides, the AHE is sensitive to noise.

The AHE enhances the image contrast, meanwhile enlarges the noise. In some cases, enhancement will lead to image distortion in some detail area, which effects the clinicians examine the enhanced image [16,17]. We must enhance the contrast of image, at the same time restrict the magnified noise. Thus limiting contrast function to AHE in every block will generate transform function, respectively. How
much percent of contrast will be restricted? It is need to preliminary adjustment for each the image block. Then, we define the limit function to limiting the gray level probability density, and adjust the exceed histogram to restrict noise.

E. Global Gain Adjustment

We present a global gain adjustment technique in our investigation for histogram equalization enhances all pixels uniformly. We employ the mean introduced in [3,15] to accomplish this non-linear operation. The global gain adjustment function can be expressed as:

\[ f(z) = a[\text{sigm}(c(z - b)) - \text{sigm}(-c(z + b))] \]  

where \( a = \frac{1}{\text{sigm}(c(1-b)) - \text{sigm}(-c(z+b))} \) subject to \( 0 < b < 1 \) where \( b \) and \( c \) is rate coefficients of enhancement, and can be set values following the practical testing experiment to adaptively adjust. And the \( \text{sigm}(z) \) is described as follows:

\[ \text{sigm}(z) = \frac{1}{1 + e^{-z}} \]  

III. EXPERIMENTAL RESULTS AND DISCUSSION

The proposed algorithm has been applied to about 10 mammographic images being 1944 × 3072 sizes from the Angell Medical ADM-600 MG. The testing procedure has been implemented in MatLab2012a. To demonstrate the effectiveness of our method, we compare it with the existing popular methods of histogram equalization (HE), adaptive histogram equalization (AHE) and the method based on morphology and wavelet transform. Furthermore, we take advantage of the metrics of contrast and SNR and Contrast Improvement and Index (CII) to measure the quantitative performance analysis of proposed method.

A. Contrast Evaluation Criterion for Image

The contrast of enhanced image is evaluated to employ the metric function, and is given as follows:

\[ C_c = \frac{1}{MN} \sum_{i=1}^{M} \sum_{j=1}^{N} f'^2(i, j) - \left( \frac{1}{MN} \sum_{i=1}^{M} \sum_{j=1}^{N} f'(i, j) \right)^2 \]  

where \( M \) and \( N \) are height and width of the image respectively, \( f'(i, j) \) is the enhanced image. The Larger the value of equation (10) is, the better the contrast of the image is.

B. Contrast Improvement Index (CII)

A quantitative measure of contrast enhancement can be defined by a contrast improvement index, and its formula can be expressed by the following:

\[ \text{CII} = \frac{C_{\text{processed}}}{C_{\text{origin}}} \]  

where \( C_{\text{processed}} \) and \( C_{\text{origin}} \) are the contrasts of the processed and original images, respectively. \( C \) is the average value of the local contrast in the processed or original region.

The local contrast at each pixel is measured as \((X_{\text{max}} - X_{\text{min}})/(X_{\text{max}} + X_{\text{min}})\) in its local window size. We applied a version of the optical definition of contrast demonstrated in [8]. The contrast \( C \) of an image is described as follows.

\[ C = \frac{m_f - m_b}{m_f + m_b} \]  

where \( m_f \) is the mean luminance value of the foreground and corresponding \( m_b \) is equal to the mean luminance value of background. In our experiment, we use the 5 × 5 local windows. The greater value of CII gives a much better indication of image quality and the value CII of original image is 1.0000.

C. Results and Discussion

As shown in Fig. 3 and 4, they are one of different persons mammographic images. In the histogram equalization, the pixels are spreading uniformly. The traditional HE method is adopted to enhance the original image. The produced result through HE improves the contrast a little and we can identify tissue node, but the HE over amplifies the noise which results in the fibroglandular albefaction and the enhanced results can be applied to clinical. It seems to that the enhanced contrast image through AHE method is degraded in visual effective. In addition, the AHE method over enhances the original image. Although the algorithm based on wavelet transform and morphology has made the original image become smoother and made the noise of image decrease, we can almost not find out the details and tissue nodes. Hence the processed image does not play a significant role in clinical practice. The result enhanced by the proposed algorithm is not only saving good details, but also the edges are preserved and enhanced. Features and fibroglandulars are enhanced, the tissue nodes can be identified clearly in the apparent visual quality and the contrast of mammogram has been improved a lot.

In the table I and II, comparison of values of contrast, contrast improvement index and SNR shows that the proposed method outperforms the HE, AHE and the method based on wavelet transform and morphology in all the experimental images, which indicates better contrast enhancement of images. We can clearly identify that the proposed method can better enhance image contrast and preserve the detail information of image. Both visual effect and quantitative measurement have shown that the proposed method is more suitable for contrast enhancement of mammographic images.

IV. CONCLUSION

A contrast enhancement of method based on multiscale Laplacian Gaussian pyramid transform, mathematical morphology and contrast limited adaptive histogram equalization is proposed for mammographic images, which employs the penalty terms to adjust the various aspects of contrast enhancement. Thus, the proposed method enhances the image...
Fig. 3. Comparison of contrast enhancement of mammograms. (a) Original image. (b) Enhancement by histogram equalization. (c) Enhancement by adaptive histogram equalization. (d) Enhancement by the method based on wavelet transform and morphology. (e) Enhancement by the proposed algorithm.

Fig. 4. Comparison of contrast enhancement of mammograms. (a) Original image. (b) Enhancement by histogram equalization. (c) Enhancement by adaptive histogram equalization. (d) Enhancement by the method based on wavelet transform and morphology. (e) Enhancement by the proposed algorithm.

contrast at the same time effectively restricts the enlarged noise. The method was tested on mammograms, and com-
pared with the existing popular approaches of histogram equalization and adaptive histogram equalization and the method based on wavelet transform and morphology. Furthermore, experimental results show that the proposed method seems more suitable for mammographic images enhancement in both visual appearance and qualitative measurement. Besides, the enhanced results yielded by proposed method still have some insufficient in visualization and the next we experimented the proposed algorithm to mammographic images from the standard Database Mammographic Image Analysis Society (MIAS). For performance evaluation of the proposed algorithm, SNR, contrast and contrast improvement index are adopted. Experimental results and tables show that the proposed algorithm seems to yield significantly better image when compared with other well known algorithms.

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