Adaptive Mammographic Image Feature Enhancement Using Wavelet-Based Multiresolution Analysis*

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ABSTRACT

This paper presents a novel and computationally efficient approach to an adaptive mammographic image feature enhancement using wavelet-based multiresolution analysis. Upon wavelet decomposition applied to a given mammographic image, we integrate the information of the tree-structured zerocrossings of wavelet coefficients and the information of the low-pass filtered subimage to enhance the desired image features. A discrete wavelet transform with pyramidal structure has been employed to speed up the computation for wavelet decomposition and reconstruction. The spatio-frequency localization property of the wavelet transform is exploited based on the spatial coherence of image and the principle of human psychovisual mechanism. Preliminary results show that the proposed approach is able to adaptively enhance local edge features, suppress noise, and improve global visualization of mammographic image features. This wavelet-based multiresolution analysis is therefore promising for computerized mass screening of mammograms.

Keywords: Mammography, image feature enhancement, wavelet transform, multiresolution analysis, human psychovisual mechanism, image processing

1. INTRODUCTION

Early diagnosis of cancers is an essential and important step to reduce mortality from these diseases. For breast cancer, a leading cause of cancer deaths among women, screen/film mammography is currently considered to be the best and the most practical radiological technique for early detection of small breast tumors.[1] The presence of microcalcification in mammograms is of great clinical importance for radiological diagnosis. Radiologists use this type of signature to discriminate normal tissues from abnormal or cancerous ones. However, even well-trained radiologists misdiagnose mammograms by 10%-20% of what they review.[2, 3]

For a realistic mass screening of mammograms, computer-assisted diagnosis (CAD) is desired for a fast and operator-independent analysis of massive volumes of mammographic images. It has also been shown that the CAD has the potential to reduce the misdiagnosis rate.[4] In general, three operations are required in CAD, namely, noise suppression, feature enhancement, and feature extraction. There are many attempts on CAD with digital mammography.[5–11] However, adaptive and robust algorithms are still needed to integrate these operations.

Wavelet transform has recently been applied to digital mammography for feature enhancement and extraction with promising potentials.[12–16] The framework of current wavelet-based mammographic image feature enhancement and extraction follows a general pattern: image decomposition with the forward wavelet transform, linear or nonlinear processing over the wavelet coefficients, and image reconstruction with the inverse wavelet transform. In general, edge-related information [17–20] is used to guide the linear or nonlinear processing. These edges

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are often obtained from the multiscale edge detectors by smoothing the signal at various scales and detecting sharp variation points from the extrema of their first-order derivatives and the zerocrossings of their second-order derivatives. Several researchers [12, 14, 15] have presented some interesting and encouraging results using wavelet transform in digital mammography. Laine *et al.* used a 2–D dyadic wavelet transform and performed edge-related analysis on the wavelet coefficients for feature enhancement. Strickland *et al.* applied the matched filter concepts to combine with the wavelet transform for the detection of microcalcifications. Both approaches seek to process the highpass filtered subimages to extract information of maximum coefficients for enhancement purpose. These processings are executed with full resolution of images at each level without downsampling. In general, the information at different levels is processed separately without exploiting the information across different levels as well as the information in low-pass filtered subimage.

It is well known that the wavelet-based image analysis has two distinct characteristics: multiresolution and spatio-frequency localization.[21, 22] To take full advantage of the wavelet-based analysis, these two characteristics need to be optimally integrated with the desired image processing tasks. Multiresolution refers to the characteristics of the image analysis such that a feature can appear at different levels of subimages. In the case of mammographic image analysis, multiresolution analysis allows the feature enhancement and extraction to combine information from several channels at different resolution levels to obtain a robust estimate with efficient processing. With spatio-frequency localization, an abrupt change in image intensity can appear in highpass filtered subimages with accurate spatial location. This is quite different from the traditional Fourier analysis since the spatial information is lost after Fourier transform. In wavelet-filtered subimages, an isolated single-pixel intensity change can be considered as noise and should be suppressed while abrupt intensity change over relatively large regions may be considered as image irregularity or edge structures. These structures in mammographic images usually correspond to the microcalcification details that we would like to preserve.

In this paper, the framework of image analysis also follows the general pattern, that is, the enhancement is performed on the wavelet-filtered subimages. However, we integrate the information from several channels and different resolutions to maximize the potential of the multiresolution analysis and to exploit the human psychovisual mechanism. The cross-band integration is implemented by establishing a zerocrossing-tree for the purpose of adaptive feature enhancement and noise suppression. Only these coefficients within the zerocrossing-tree are considered related to mammographic features and are therefore enhanced. The low-pass filtered subimage is used to guide the enhancement process according to human psychovisual mechanism. Furthermore, instead of full resolution processing, discrete wavelet transform with pyramid structure has been employed to speed up the computation for fast wavelet decomposition and reconstruction.

The concept of zerocrossing-tree is based on our observation that the filters for highpass filtering with orthonormal or biorthogonal bases in discrete wavelet decompositions are of Laplacian-like property, i.e., they resemble the second-order-derivative operations. Therefore, zerocrossings in wavelet coefficient space describe the multiresolution edges of the original image. Because of the spatial coherence of image, the same image feature structure, in general, would appear at different level of subimages. A similar feature structure in a parent subimage can be found in its corresponding location of the child subimage so that they constitute a parent-child location relation. Such parent-child location relation can be established as zerocrossing-trees to represent evolution of the multiresolution edges. The neighborhood configuration has been introduced to obtain the adaptivity to the local intensity variation. By following the evolutions of these zerocrossings, we will be able to enhancement the desired image features while, at the same time, suppress the undesired noise.

To achieve the optimal visualization of the image structures, the enhancement of highpass filtered subimages based on zerocrossing-tree is then integrated with the enhancement of baseband subimage according to human psychovisual mechanism. It is well known that human vision follows the famous Weber's Law[23] that is, brightness discrimination is poor at low levels of illumination, and it improves significantly as the brightness illumination increases. Therefore, how to enhance a particular wavelet coefficient should also depend on the levels of illumination within its neighborhood. For low levels of illumination, large amount of enhancement is desired while for high levels of illumination, moderate amount of enhancement may be sufficient. For this same reason, the baseband subimage may also be enhanced by increasing the overall level of illumination so that the brightness discrimination is maximized.

Images used in our experiments are obtained from the Mammography Image Analysis Research Database at the University of South Florida. These 40 images have been made available by the Department of Radiology, University Hospital Nijmegen, the Netherlands. The preliminary results of enhancement on these images show that it is promising for computerized mass screening of mammograms since the proposed algorithm is able to adaptively enhance local edge features, suppress noise and greatly improve global visualization of mammographic image features.

Section 2 briefly discusses the discrete wavelet transforms used in this research with pyramid structure. Section 3 introduces the adaptive feature enhancement algorithm based on the proposed multiresolution analysis. We focus on the information integration aspect which is the key to the success of the proposed approach. Section 4 presents the experimental results and Section 5 concludes this paper with a summary and some discussion of future research direction.

2. WAVELET ANALYSIS

Unlike the windowed Fourier transform which has a fixed resolution in the spatial and frequency domains, the resolution of wavelet transform varies with a scale factor. Therefore, wavelet representations lie in between the spatial and frequency domains and provide a simple and efficient hierarchical framework for interpretation of image information from both the spatial and frequency domains. The regularity and orthogonality of wavelet bases ensure the signal reconstruction with high quality. For a discrete wavelet decomposition of a given 1–D signal f with a mother wavelet ψ and a scaling function ϕ, we have the following relations:[22]

$$\begin{aligned} f &= \sum c_{m,n}(f)\psi_{m,n} \\ c_{m,n}(f) &= \langle \psi_{m,n}, f\rangle = \sum_k g_{2n-k} a_{m-1,k}(f) \\ a_{m,n}(f) &= \sum_k h_{2n-k} a_{m-1,k}(f) \end{aligned} \tag{1}$$

where $g_l = (-1)^l h_{1-l}$ and $h_n = \sqrt{2}\int \phi(x-n)\phi(2-x)dx$. For the orthonormal wavelet bases the exact reconstruction can be written as:

$$a_{m-1,l}(f) = \sum_n \left[h_{2n-l} a_{m,n}(f) + g_{2n-l} c_{m,n}(f)\right]. \tag{2}$$

Equation (2) is a recursive relation which facilitates a fast computation algorithm. In the case of biorthogonal wavelet bases, the reconstruction becomes[24]

$$a_{m-1,l}(f) = \sum_n \left[\tilde{h}_{2n-l} a_{m,n}(f) + \tilde{g}_{2n-l} c_{m,n}(f)\right] \tag{3}$$

where the decomposition and reconstruction filters satisfy:

$$\begin{aligned} \tilde{g}_n &= (-1)^n h_{1-n} \\ g_n &= (-1)^n \tilde{h}_{1-n} \\ \sum_n h_n \tilde{h}_{n+2k} &= \delta_{k,0} \end{aligned} \tag{4}$$

According to Mallat[22], 2–D wavelet representations for images can be similarly constructed with a separable 2–D wavelet transform. The implementation of 2–D discrete wavelet decomposition is shown in Fig.1. Each level consists of four subimages denoted as LL, LH, HL and HH. LH exhibits the horizontal components (vertical edges), HL the vertical components (horizontal edges), and HH the components in both directions (corners). The LL corresponds the lowest frequencies and represents the local DC components of the original image. Because of the bandwidth reduction after wavelet filtering, the resultant subimages may be downsampling to allow fast computation in the process of enhancement. Fig. 2(a) shows the arrangement of subimages after discrete wavelet decomposition and downsampling.

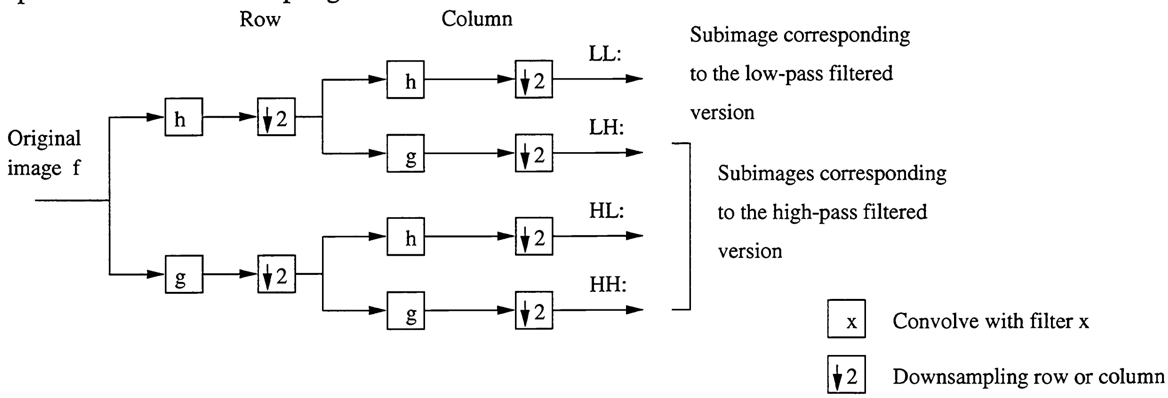


Figure 1. Implementation of 2D discrete wavelet decomposition.

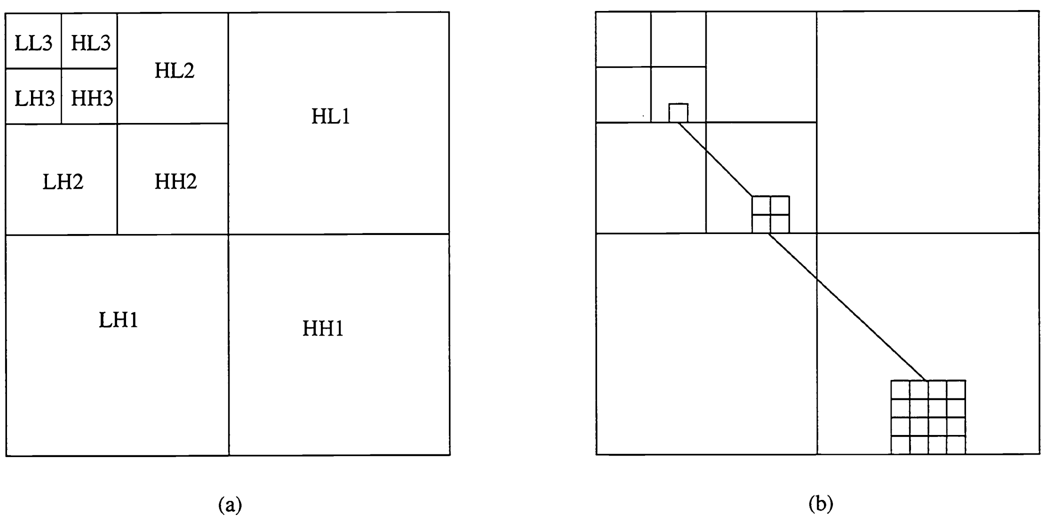


Figure 2. (a) Subimage arrangements of wavelet decomposition; (b) Parent-child relations.

We choose short filters to enable fast computation. The shortest wavelet filters are those corresponding to the Haar basis, i.e., $h_0 = h_1 = \sqrt{2}$, $g_0 = -g_1 = \sqrt{2}$ and all other $h_n, g_n = 0$. However, such filters result in less smoothness and lower efficiency in exploiting the spatial coherence of image structures in contrast to the spatial randomness of noise. In many image processing applications, smooth wavelet filters are desired to obtain better localization properties in both spatial and frequency domains. Therefore, a trade-off between the computational speed and the characterization of image features is usually needed for a specific application. In this research, we adopt the "Laplacian filters" (5/7) [24] for the discrete wavelet transform because these filters are nearly orthonormal with moderate lengths.

3. ENHANCEMENT ALGORITHM

Once a mammographic image is decomposed with the given wavelet filter, the baseband subimage is essentially the replica of the original image with lower spatial resolution. However, the highpass filtered subimages with different directional filtering and at different resolution levels would exhibit various edges corresponding to the filter directions and the resolution levels. A distinct feature of this approach different from existing ones is that we not only perform the enhancement on the individual highpass filtered subimages but also integrate the information from corresponding subimages at different levels using the parent-child relation and the information from baseband subimages according to human psychovisual mechanism.

In this section, we will first summarize some characteristics of the wavelet-based multiresolution analysis. We will then describe the proposed adaptive enhancement scheme designed to take full advantage of these characteristics to achieve optimal integration of information from different channels.

3.1 CHARACTERISTICS

There are several distinct characteristics of the wavelet-filtered subimages that can be exploited in the design of an integrated adaptive enhancement algorithm. In this research, we will explore three such characteristics: the baseband subimages, the zerocrossings, and the parent-child location relations of the zerocrossing tree. Once these characteristics are carefully explored and the information from different channels are integrated, we expect to achieve better performance in image enhancement.

Unlike existing approaches in which baseband subimage has not been used for feature enhancement, the proposed enhancement algorithm will incorporate the information from baseband subimages to maximize the visual effect of enhancement. The incorporation of baseband subimage will involve two types of operations: (1) global shift of baseband intensity value; and (2) highpass subimages enhancement weighted by the corresponding intensity value at baseband. Both operations are based on the Weber's Law of visual perception. An appropriate global shift of baseband intensity value will ensure that the reconstructed images would be bright enough to perceive the subtle brightness discriminations. Since the wavelet-based enhancement can be implemented by scaling the wavelet coefficients in highpass subimages, the weighting of baseband intensity value on the scaling implies that the algorithm is adaptive to the local illumination levels. This is important since according to human psychovisual mechanism, in particular the Weber's Law, the brightness discrimination is poor at low levels of illumination, and it improves significantly as illumination increases. Therefore, an inverse weighting would be suitable so that, for same edge strength, large scaling is needed when the baseband intensity is low, and small scaling will be adequate when the baseband intensity is high. It is evident that both operations would be subject to the dynamic range limitation of the display devices.

In their classical paper[20], Marr and Hildreth have shown that the position of multiscale sharp variation points can be obtained from the zerocrossings of the signal convolved with the Laplacian of a Gaussian. In the case of mammographic images, the image features, such as microcalcifications, actually correspond to the intensity discontinuities. We noticed that the filters for LH, HL and HH highpass filtering with orthonormal or biorthogonal bases, except Haar bases, in discrete wavelet decompositions are of Laplacian-like property, a second-order-derivative operation. The zerocrossing properties are still well preserved in these highpass filtered subimages even with downsampling in the pyramidal structure. Fig. 3 shows examples of the zerocrossings of a given image using "spline filters" and "Laplacian filters".[24] Notice that these zerocrossings correspond to potential edges of the original image at multiresolution levels. Therefore, we assert that the zerocrossings in the highpass filtered subimages are equivalent to the multiresolution edges of the original image. The multiresolution position information of the edges can be obtained from processing of the zerocrossings of wavelet coefficients in the highpass-filtered subimages.

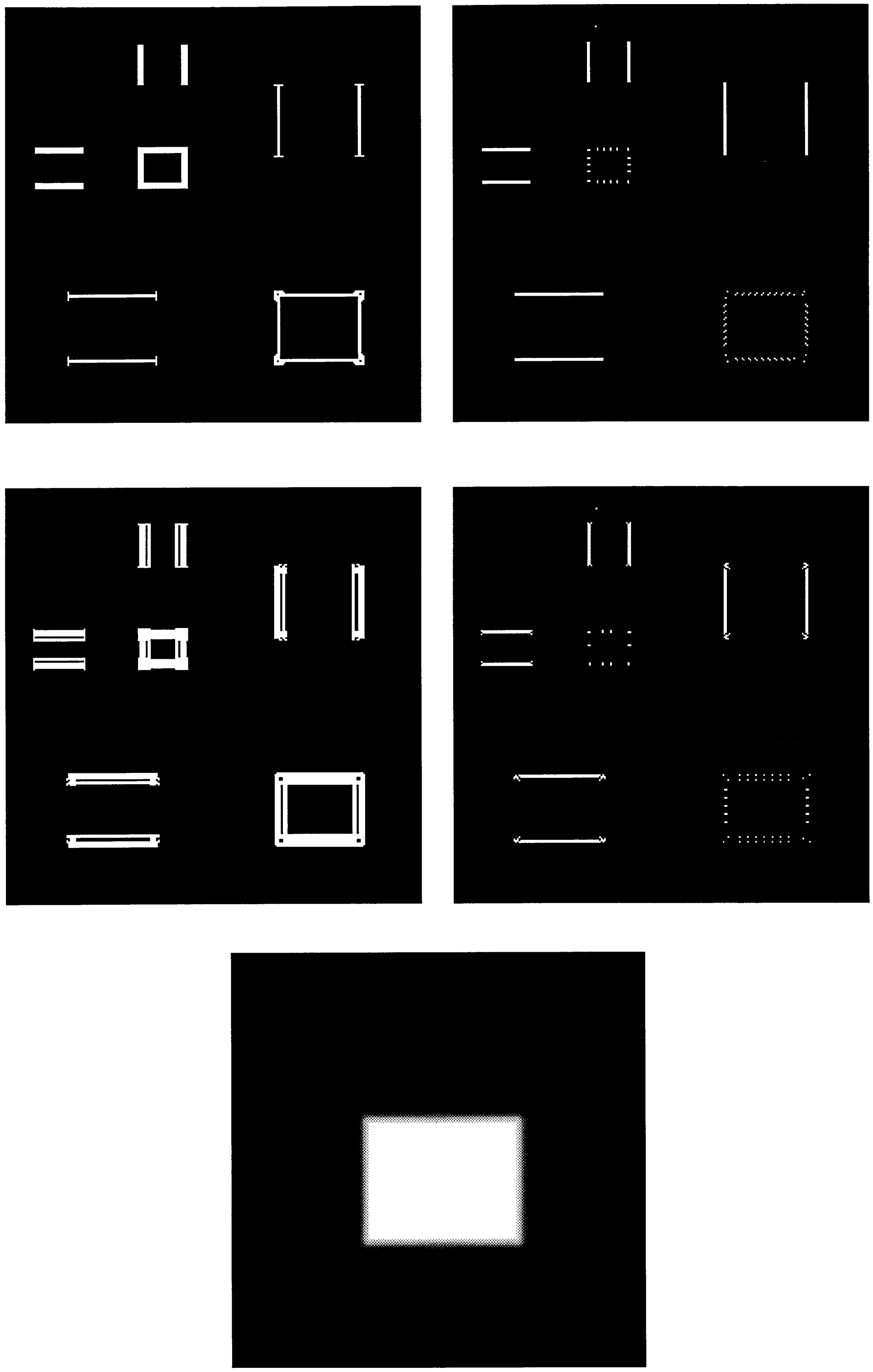


Figure 3. The bottom is a given image. The left and right are zerocrossings before and after neighborhood processing using "Laplacian filters" (upper) and "spline filters" (middle) in wavelet decomposition.

Because of the spatial coherence of image, image feature structures, in general, would appear at different level of subimages. If we define a parent-child relation of subimage as relationship between subimages at specific resolution level and the corresponding subimages at a finer resolution level, then, an image feature structure in a parent subimage would have similar image features in its child subimage at corresponding locations. Such parent-child location relation is shown in Fig. 2(b). This parent-child spatial coherence relation can be very useful in zerocrossing analysis, since, for medical images, an isolated single-pixel intensity change in wavelet-filtered subimages can be considered as noise and should be suppressed while abrupt intensity changes over a relatively large connected region may be considered as clinically important structures. For mammographic images, these coherent features usually correspond to the microcalcification details and should be preserved and preferably visually enhanced. On the other hand, this parent-child relation may also be used to suppress mammographic image noise because, as suggested by several researchers[17, 18, 25] that sharp variation point of image intensity which do not propagate to coarser scales can be removed for noise suppression.

3.2 ADAPTIVE ENHANCEMENT ALGORITHM

The proposed adaptive enhancement scheme is shown in Fig. 4. Upon the completion of wavelet filtering and downsampling to a desired decomposition level, the adaptive enhancement scheme can be applied to these decomposed subimages. There are three basic steps in this proposed enhancement algorithm: zerocrossing detection, zerocrossing-tree establishment, and integrated adaptive enhancement. With zerocrossing detection, we are able to locate the accurate position of the image features within each subimages. Since not all edges are considered useful features for mammographic image enhancement, we establish the zerocrossing-tree according to the spatial coherence of image features. Only these edges within this zerocrossing-tree will be enhanced to ensure that the mammographic image features, not the image noises, are indeed enhanced. Furthermore, to achieve an optimal visualization of the features governed by Weber's Law, the baseband information is also incorporated into the enhancement algorithm.

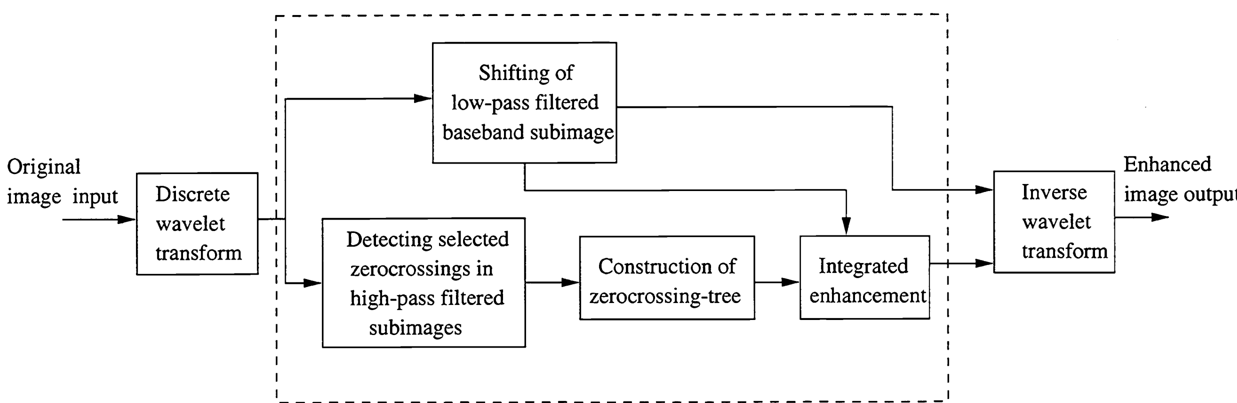
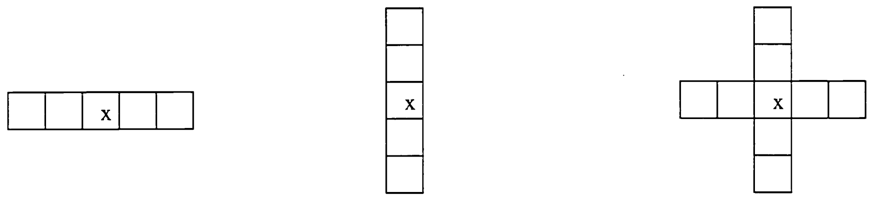


Figure 4. A wavelet-based adaptive feature enhancement approach.

As we have discussed, the zerocrossings in subimages characterize the edge structure of the image. These edges correspond to potential microcalcifications and therefore need to be enhanced. Among the zerocrossings in the highpass filtered subimages, those with locally maximum variation rate of wavelet coefficients is important to represent the local edge features. To locate these zerocrossing, we introduce neighborhood configurations for the algorithm to achieve its adaptivity to the local intensity variation. Three types of neighborhood configuration are used in this research, namely, a horizontal 1–D neighborhood, a vertical 1–D neighborhood and a crossbar 2–D neighborhood, as shown in Fig. 5. These configurations correspond to the highpass filters used in wavelet decomposition: horizontal filter for LH subimage, vertical filter for HL subimages, and diagonal for HH subimage.

With these neighborhood mask, zerocrossings pass through the local maximum variation rate test will be assigned as "selected zerocrossing" and will be used in the next step of processing.



(a) (b) (c)

Figure 5. Neighborhood for (a) HL subimage processing, (b) LH subimage processing and (c) HH subimage processing. x is the selected zerocrossing if it has maximum variation rate in the neighborhood.

The next step of processing aims at recognizing the spatial coherence of the image features from the selected zerocrossings to establish a zerocrossing-tree. A "selected zerocrossing" is considered part of the zerocrossing-tree if it passes the parent-child location relationship test. That is, a "selected zerocrossing" will be attached to the zerocrossing-tree if its parent is also a "selected zerocrossing" and descends from the root of the zerocrossing-tree. With this spatial coherence test, the zerocrossings in the zerocrossing-trees will include those image structure with parent-child location relationship rather than the noise which would not have such relationship due to its randomness nature. The established zerocrossing-trees represent the evolution of edge structure from coarse resolution level to fine resolution levels. In the case of adaptive enhancement of mammographic images, only these wavelet coefficients corresponding to zerocrossings within the zerocrossing-tree are scaled to achieve the desired enhancement results.

Once the zerocrossing-tree is established, the information from baseband can be integrated with the enhancement in the highpass-filtered subimages. In the case of global shift of baseband intensity value, if needed, an appropriate constant is added to every pixels in the baseband to increase the overall brightness so that subtle discrimination can be perceived after shift. In the case of weighted enhancement of highpass subimages, the weighting function will be inversely proportional to the illumination levels in the corresponding neighborhood in baseband subimages. Such operation allows the radiologists to achieve a balanced brightness discrimination across the whole dynamic range of the display device.

If we denote $E^a_{m,n}$ and $E^c_{m,n}$ as the proposed operators for processing low-pass filtered (baseband) and highpass filtered components, respectively, with the spatial position n and at level m, the reconstruction of the enhanced subimages can be written as:

$$\begin{aligned} \bar{a}_{m-1,l}(f) &= \sum_n \left[\tilde{h}_{2n-l} E^a_{m,n}(a_{m,n}(f)) + \tilde{g}_{2n-l} E^c_{m,n}(c_{m,n}(f))\right] \\ &= a_{m-1,l}(f) + \sum_n \left[\tilde{h}_{2n-l}\big(E^a_{m,n}(a_{m,n}(f)) - a_{m,n}(f)\big) + \tilde{g}_{2n-l}\big(E^c_{m,n}(c_{m,n}(f)) - c_{m,n}(f)\big)\right]. \end{aligned} \tag{5}$$

For baseband enhancement, the shift can be easily defined as:

$$E^a_{m,n}(a_{m,n}(f)) = a_{m,n}(f) + b \tag{6}$$

where b is a shift constant. Such overall shift will be able to preserve the relative gray level distribution of the original image. For weighted scaling used in the enhancement of highpass subimages, the weighting function can be written as:

$$P(x_{m,n}) \propto \left(\alpha \sum_{s \in N_n} x_{m,s} + \beta\right)^{-1} \tag{7}$$

where α and β are constant parameters, N_n represents a defined neighborhood for position n. With such weighting function the enhancement operator can be expressed as:

$$E^c_{m,n}(c_{m,n}(f)) = P(a_{m,n}(f)) \cdot c_{m,n}(f) \quad \text{if} \quad c_{m,n}(f) \quad \text{in zerocrossing-tree}. \tag{8}$$

4. EXPERIMENTAL RESULTS

Images used in our experiments are obtained from the Mammography Image Analysis Research Database at the University of South Florida. These 40 images have been made available by the Department of Radiology, University Hospital Nijmegen, the Netherlands. For the convenience of display, the original images have been subsampled and resulted in 512 x 512 images. In this experiment, "Laplacian filters (5/7)" [24] are selected to compute discrete wavelet transform because the filters are nearly orthonormal filters with moderate lengths. The width or height of the neighborhood mask has been chosen the same as the length of wavelet filters since this has been shown to produce empirically better results. *Prior* information about microcalcification details in mammographic image is used to guide the choice of desired decomposition levels. Some typical experimental results on the images from the database are shown in Fig. 6.

It is evident from Fig. 6 that the shifting processing for baseband subimage improves global visualization over the original images. Together with the weighted scaling using the illumination level of the baseband subimage, the proposed enhancement scheme is able to make some unseen or barely seen features visible. The zerocrossing-tree based processing allows us to enhance those structures in which we are interested while suppress noise.

5. SUMMARY

We have presented a novel and computationally efficient approach to adaptive mammographic image feature enhancement and noise suppression using wavelet-based multiresolution analysis. We integrate information of the tree-structured zerocrossing of wavelet coefficients and information of the low-pass filtered subimage to achieve robust and optimal enhancement. The spatio-frequency localization property of the wavelet transform is exploited based on the spatial coherence of image and the principle of human psychovisual mechanism. Preliminary results show that the proposed approach is able to adaptively enhance local edge features, suppress noise, and improve global visualization of mammographic image features. This wavelet-based multiresolution analysis is therefore promising for computerized mass screening of mammograms.

This multiresolution analysis scheme can be extended to feature extraction applications to extract microcalcifications from mammographic images. By incorporating the shape and size knowledge of the microcalcification, we will be able to develop a robust feature extraction algorithm suitable for computerized mass screening of mammograms as well as computer-aided-diagnosis with real time implementation potential.

REFERENCES

1. A. tucker and P. Last, "Cancer screening and research," *Physicians Bulletin*, vol. 39, pp. 190–191, 1988.
2. H. A. Frazer, "Computerized diagnosis comes to mammography," *Diagnostic Imaging*, pp. 91–95, June 1991.
3. L. Tabar and P. B. Dean, "Basic principles of mammographic diagnosis," *Diagn. Imag. Clin. Med.*, vol. 54, pp. 146–157, 1985.
4. A. G. Gale, S. M. Astley, D. R. Dance, and A. Y. Cairns, eds., *Digital mammography*. Amsterdam, Netherlands: Elsevier Science B. V., 1994.

5. A. P. Dhawan and E. L. Royer, "Mammographic feature enhancement by computerized image processing," *Comput. Methods and Programs in Biomed.*, vol. 27, no. 1, pp. 23–35, 1988.

6. D. Brzakovic, X. M. Luo, and P. Brzakovic, "An approach to automated detection of tumors in mammograms," *IEEE Trans. Medical Imaging*, vol. 9, pp. 232–241, September 1990.

7. H. P. Chan, K. Doi, S. Galhotra, C. J. Vyborny, and H. M. ahd P. M. Jokich, "Image analysis and computer-aided diagnosis in digital radiography. automated detection of microcalcifications in mammogaphy," *Medical Physics*, vol. 14, pp. 538–548, July 1987.

8. H. P. Chan, K. Doi, C. J. Vyborny, K. L. Lam, and R. A. Schmidt, "Computer-aided detection of microcalcifications in mammograms," *Investigative Radiology*, vol. 23, pp. 664–671, September 1988.

9. S. Lai, X. Li, and W. F. Bischof, "On techniques for detecting circumscribed masses in mammograms," *IEEE Trans. Medical Imaging*, vol. 8, pp. 377–386, December 1989.

10. R. Gordon and R. M. Rabgayyan, "Feature enhancement of film mammograms using fixed and adaptive neighborhoods," *Applied Optics*, vol. 23, pp. 560–564, February 1984.

11. A. Giles, A. R. Cowen, and G. J. S. Parkin, "A clinical workstation for digital mammography," in *Proc. SPIE*, vol. 1905, pp. 806–817, 1993.

12. A. F. Laine, S. Schuler, J. fan, and W. Huda, "Mammographic feature enhancement by multiscale analysis," *IEEE Trans. Medical Imaging*, vol. 13, pp. 725–740, December 1994.

13. W. B. Richardson, "Nonlinear filtering and multiscale texture discrimination for mammograms," in *Proc. SPIE Conf. Mathematical Methods in Medical Imaging*, vol. 1768, (San Diego, CA), pp. 293–305, July 1992.

14. A. Laine and S. Song, "Wavelet processing techniques for digital mammography," in *Proc. SPIE Conf. Visualization in Biomedical Computing*, vol. 1808, (Chapel Hill, NC), pp. 610–624, October 1992.

15. R. N. Strickland and H. I. Hahn, "Wavelet transform matched filters for the detection and classification of microcalcifications in mammography," in *Proc. IEEE Int. Conf. Image Processing*, vol. II, (Washinton, D.C.), pp. 422–425, October 1995.

16. W. Qian and L. P. Clarke, "Adaptive multistage nonlinear filtering and wavelet for medical image enhancement," in *Proc. IEEE Int. Conf. Image Processing*, vol. II, (Austin, TX), pp. 711–715, November 1994.

17. S. Mallat and S. Zhong, "Characterization of signal from multiscale edges," *IEEE Trans. Pattern Analysis and Machine Intelligence*, vol. 14, pp. 710–732, July 1992.

18. S. Mallat, "Zero-crossing of a wavelet transform," *IEEE Trans. Information Theory*, vol. 37, pp. 1019–1033, July 1991.

19. J. Canny, "A computational approach to edge detection," *IEEE Trans. Pattern Analysis and Machine Intelligence*, vol. 8, pp. 679–698, November 1986.

20. D. Marr and E. Hildreth, "Theory of edge detection," in *Proc. Roy. Soc. Lon.*, vol. 207, pp. 187–217, 1980.

21. I. Daubechies, "The wavelet transform, time-frequency localization and signal analysis," *IEEE Trans. Information Theory*, vol. 36, pp. 961–1005, 1990.

22. S. G. Mallat, "A theory for multiresolution signal decomposition: The wavelet representation," *IEEE Trans. Pattern Analysis and Machine Intelligence*, vol. 11, pp. 674–693, July 1989.

23. R. C. Gonzalez and R. E. Woods, *Digital image processing*. Reading, MA: Addison-Wesley, 1992.

24. A. Cohen, I. Daubechies, and J. C. Feauveau, "Biorthogonal bases of compactly supported wavelets," *AT&T Bell Lab., Tech. Rep., TM 11217-900529-07*, 1990.

25. S. Mallat and W. L. Hwang, "Singularity detection and processing with wavelet," *IEEE Trans. Information Theory*, vol. 38, pp. 617–643, March 1992.

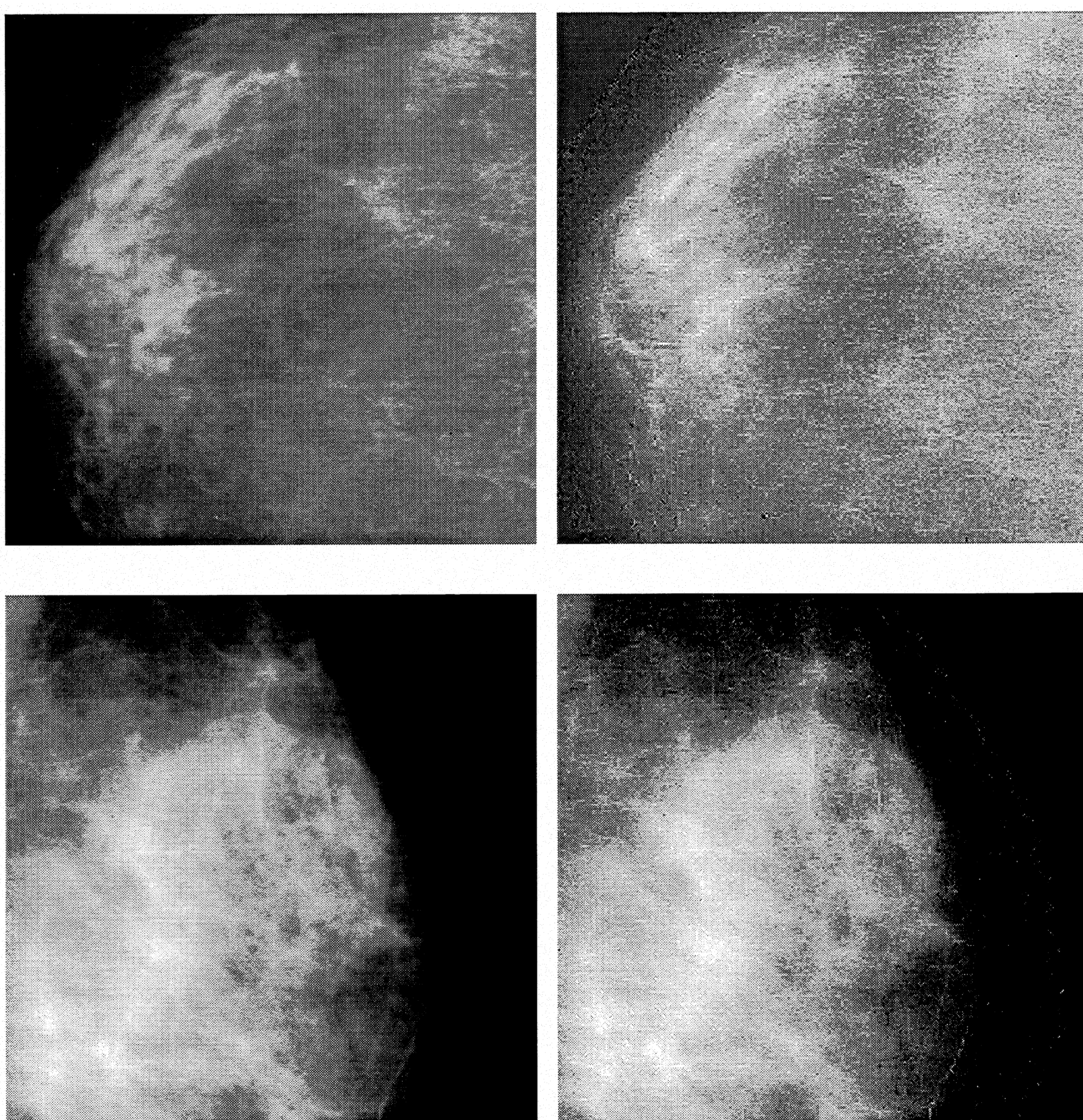


Figure 6. Experimental results, the left are original images and the right are enhanced images. (Continued . . .)

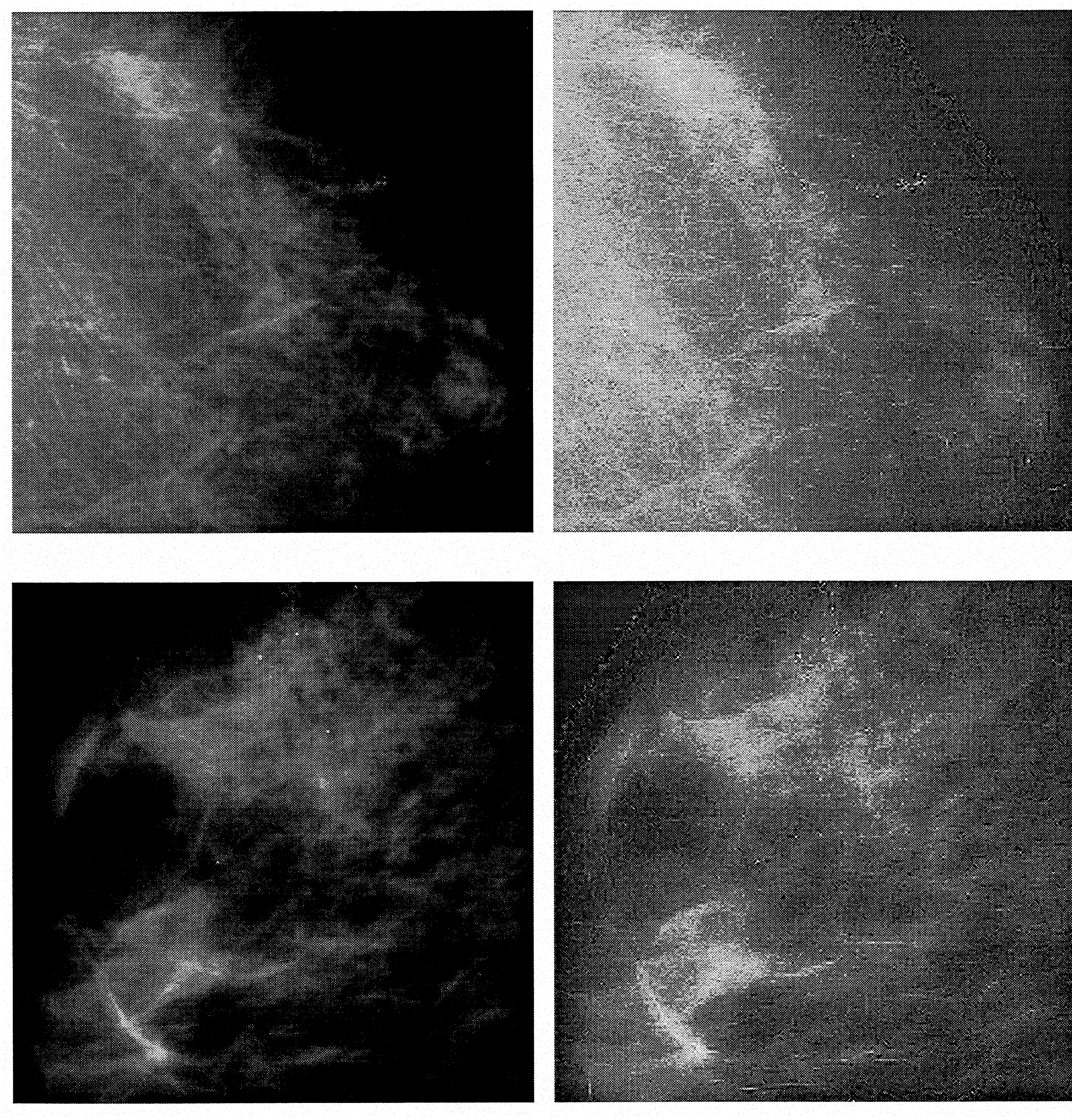


Figure 6. Experimental results, the left are original images and the right are enhanced images.