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Mammographic Images Using Two-Dimensional MultiWavelet Transform With Multiresolution Analysis

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***Abstract*—In this paper a new image enhancement scheme using wavelet with multi-resolution analysis is presented. This analysis approximately divides the image into several sub bands containing features at different scales. The advantage of a multi-resolution decomposition of mammograms is that small features like micro calcifications will be prominent in one sub band, whereas larger features like masses will be dominant in a different sub band. Further, the result at the coarse scale is used as an initial contour on a finer image and so on, until the negative image resolution is reached. This continuation method in the wavelet domain detects the lesions in mammographic images more accurately.**

***Keywords*—Image Segmentation, Mammograms, Multiresolution.**

I. INTRODUCTION

A. Mammography

It is the process of using low-energy-X-rays (usually around 30 kVp) to examine the human breast and is used as a diagnostic and a screening tool. The goal of mammography is the early detection of breast cancer, typically through detection of characteristic masses and/or micro calcifications. Most doctors believe that mammography reduces deaths from breast cancer, although a minority does not.

In many countries routine mammography of older women is encouraged as a screening method to diagnose early breast cancer. In 2009, the U.S. Preventive Services Task Force (USPSTF) recommended that women with no risk factors have screening mammographies every 2 years between age 50 and 74. They found that the information was insufficient to recommend for or against screening between age 40 and 49 or above age 74. Altogether clinical trials have found a relative reduction in breast cancer mortality is of 20%. Some doctors believe that mammographies do not reduce deaths from breast cancer, or at least that the evidence does not demonstrate it.

Like all x-rays, mammograms use doses of ionizing radiation to create images. Radiologists then analyze the image for any abnormal findings. It is normal to use lower energy X-rays (typically Mo-K) than those used for radiography of bones. At this time, the modality of mammography along with physical breast examination is choice for screening for early breast cancer. Ultrasound, ductography, positron emission mammography (PEM) and magnetic resonance imaging are adjuncts to mammography. Ultrasound is typically used for further evaluation of masses found on mammography or palpable masses not seen on mammograms [2]. Ductograms are still used in some institutions for evaluation of bloody nipple discharge when the mammogram is non-diagnostic. MRI can be useful for further evaluation of questionable findings as well as for screening pre-surgical evaluation in patients with known breast cancer to detect any additional lesions that might change the surgical approach, for instance from breast-conserving lumpectomy to mastectomy. New procedures, not yet approved for use in the general public, including breast to mosynthesis may offer benefits in years to come. Breast self-examination (BSE) was once promoted as a means of finding cancer at a more curable stage. However, it has been shown to be ineffective, and is no longer routinely recommended by health authorities for general use. Awareness of breast health and familiarity with one's own body is typically promoted instead of self-exams. Mammography has a false-negative (missed cancer) rate of at least 10 percent. This is partly due to dense tissues obscuring the cancer and the fact that the appearance of cancer on mammograms has a large overlap with the appearance of normal tissues.

B. Procedure

During the procedure, the breast is compressed using a dedicated mammography unit. Parallel-plate compression evens out the thickness of breast tissue to increase image the quality by reducing the thickness of tissue that x-rays

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must penetrate, decreasing the amount of scattered radiation (scatter degrades image quality), reducing the required radiation dose and holding the breast still (preventing motion blur). In screening mammography, both head-to-foot (craniocaudal, CC) view and angled side-view (mediolateral oblique, MLO) images of the breast are taken. Diagnostic mammography may include these and other views, including geometrically magnified and spot-compressed views of the particular area of concern. Deodorant, talcum powder or lotion may show up on the X-ray as calcium spots, and women are discouraged from applying these on the day of their exam.
Until some years ago, mammography was typically performed with screen-film cassettes. Now, mammography is undergoing transition to digital detectors, known as digital mammography or Full Field Digital Mammography (FFDM). The first FFDM system was approved by the FDA in the U.S. in 2000. This progress is some years later used in general radiology on vies of the factors:

1. the higher spatial resolution demands of mammography,
2. significantly increased expense of the equipment,
3. concern by the FDA that digital mammography equipment demonstrate that it is at least as good as screen-film mammography at detecting breast cancers without increasing breast dose or the number of women recalled for further evaluation.

As of March 1, 2010, 62% of facilities in the United States and its territories have at least one FFDM unit. (The FDA includes computed radiography units in this figure.)
In order to encourage the use of mammograms as a screening measure for breast cancer, a number of hospitals, cancer centers and other healthcare groups have started mobile mammography vans to bring affordable, accessible and convenient mammograms to their communities. Many mobile mammography vans prioritize serving uninsured, low-income and/or non-English-speaking women who otherwise could not afford a mammogram or who are unaccustomed to seeing a doctor. Many offer free or low-cost mammograms to women who are uninsured and/or cannot afford a mammogram.

II. DIMENSIONAL MULTIWAVELET TRANSFORM WITH MULTIRESOLUTION ANALYSIS

Multiwavelet bases of multiplicity 2 provide a multiresolution analysis {Vn}nЄz of L2 using the multiscaling function as in equation (1)

$$(\emptyset(t)\,)^{\bar{}} = [[\emptyset\_0\ (t), \emptyset(t)\ ]\hat{}T \qquad (1)$$

and Multiscaling function as in equation (2)

$$\overline{\psi(t)} = [\psi_0(t), \psi_1(t)]^T \qquad (2)$$

The j^{th} scaling space is given as in equation (2) and equation (3)

$$V_j = \underset{k\epsilon z}{Span}\{\phi_0(2^j t - k), \phi_1(2^j t - k)\}$$
$$V_w = \underset{k\epsilon z}{Span}\{\psi_0(2^j t - k), \psi_1(2^j t - k)\} \qquad (3)$$

where $V_j \perp W_j$. For the case where r = 2, the multiscaling function satisfies the following 2-scale equation (4)

$$\overline{\phi(t)} = \sqrt{2}\sum_{k=0}^{l-1} H(k)\overline{\phi(2t - k)} \qquad (4)$$

where the matrix filter H [k] has one 2×2 matrix coefficients, the k^{th} matrix coefficient is given as in equation (5)

$$H[k] = \begin{bmatrix} h_0(2k) & h_0(2k+1) \\ h_1(2k) & h_1(2k+1) \end{bmatrix} \qquad (5)$$

Such that as in equation (6)

$$\sum_k h_0(k)^2 = 1 \;\; and \;\; \sum_k h_0(k)^2 = 1$$

Corresponding multiwavelet function satisfies the following equation (6)

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$$\overline{\psi(t)} = \sqrt{2}\sum_{k=0}^{l-1} G(k)\overline{\phi(2t-k)} \qquad (6)$$

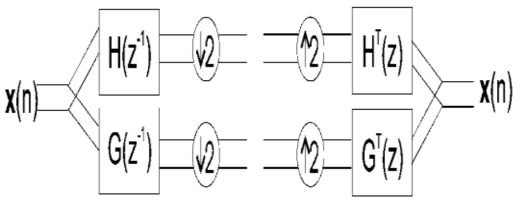
Where the matrix filter G[k] has one 2×2 matrix coefficients;
the kth matrix coefficient is given by equation (7)

$$G[k] = \begin{bmatrix} g_0(2k) & g_0(2k+1) \\ g_1(2k) & g_1(2k+1) \end{bmatrix} \qquad (7)$$

Such that

$$\sum_k g_0(k)^2 = 1 \ \ and \ \sum_k g_0(k)^2 = 1$$

For the balanced multiwavelets, h_0 and h_1 are low pass FIR filters while, g_0 and g_1 are band pass or high pass FIR filters. The perfect reconstruction multiwavelet filter bank is shown in Figure 1. If coefficient S_0



(a) Analysis section **(b) Synthesis section.**

Fig 1 The perfect reconstruction multiwavelet filter bank

(at scale zero) are input to the analysis section of the filter bank, one iteration computes the coarse vector coefficients s_{-1} and the detail vector coefficients d_{-1} at scale d_{-1} as shown in equations 8 and 9, respectively. This decomposition corresponds to the discrete multiwavelet transform.

$$\overline{s_{-1}}[n] = \sum_k H[k-2n]\overline{s_0}[k] \qquad (8)$$

$$\overline{d_{-1}}[n] = \sum_k G[k-2n]\overline{s_0}[k] \qquad (9)$$

The corresponding synthesis equation reconstructs s_0 from s_{-1} and d_{-1} using equation 10. This corresponds to the inverse discrete multiwavelet transform and is equivalent to the IDWT.

$$\overline{s_{-1}}[n] = \sum_k H^T[n-2k]\overline{s_{-1}}[k] + \sum_k G^T[n-2k]\overline{d_{-1}}[\qquad (10)$$

III. PREPROCESSING

The low pass filter H and high pass filter G in the multiwavelet filter bank are 2×2 matrices need to be convolved with two rows of data. One solution to this problem is simply to repeat the input [3,4]. But this solution is equivalent to over sampling and increases the computational complexity of the transform. Another approach is to split the input into two polyphase components, thereby maintaining critical sampling [3,1].

IV. BALANCING

If the zero-order polynomial x = [· · ·, 1, 1, 1, 1 · ··] is preserved by the low pass branch, *x* is an eigen signal of the low pass branch. Such a multiwavelet is said to be balanced to order 1[5]. Not all multiwavelets are balanced. The balanced multiwavelets do not require a pre-processing stage for the input.

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V. SHUFFLING

For unbalanced multiwavelets, a one-level decomposition shows that a large amount of similarity exists in the 2×2 blocks that comprise the LiHj, LiHj and HiHj sub bands. To restore the spatial dependencies, we interleave the high frequency sub bands XiYj (XiYj LiLj) into a single block XY. Thus, blocks LH, HL and HH are generated. This interleaving procedure is called shuffling [6]. The need and process of shuffling are illustrated in figures 3 and 4.

A. Donoho's ALGORITHM IMPLEMENTED

The Discrete Multiwavelet Transform used here are unbalanced multiwavelet (GHM order 2) and balanced multiwavelet (Cardinal balanced order 2). At first, 5-levels redundant wavelet decomposition of the original mammogram cutout is performed. Mammogram images were obtained by scanning the X-ray images in 30 micrometre X 30 micrometer resolution, 12 bits per pixel. Typical size of micro calcification varies from 0.1 mill micron to more than 1 mill micron, which corresponds to the range from the smallest 3x3 pixel round objects to more than 30 pixels wide irregular shapes. The 5-octaves analysis is taken to cover the whole range. Fine breast tissue structure and micro calcifications are almost invisible in dense parts of the original image, especially if gray-value does not cover the necessary dynamic range. Visual inspection of wavelet coefficient images show that first-level detail coefficients (HH, HL and LH) contain mostly noise. Detail coefficients in levels 2 to 5 contain fine breast structure and micro calcifications (together with some noise). Finally, level 5 approximation coefficients (LL) contain low frequency background, which corresponds to the tissue density. Reconstructed sub-images (after applying reconstruction part of filter bank) are additive components of the original image, so the reconstructed details HH^r, HL^r and LH^r at observed level were added in a single representation.
Multiwavelet decomposition requires shuffling as discussed above, otherwise the sub bands will be at different locations and thresholding followed by reconstruction may not be possible. Thresholding used here is Donoho's soft thresholding popularly known as wavelet shrinkage technique [7,8]. If additive noise is observed in the form as shown in equation (11)

$$x_i = s_t + \sigma_n n_{i,} = 1, \ldots \ldots N \qquad (11)$$

where signal s_i is corrupted by zero mean, Gaussian noise n; with standard deviation σ_n, then the risk of the so called soft - thresholding scheme is given in equation(12)

$$\begin{gathered} x = DWT(x) \\ \hat{x} = sign(|x|)(|x|) - thr), |x| \geq thr \quad otherwise \\ \hat{x} = DWT^{-1}(x) \end{gathered} \qquad (12)$$

is within a logarithmic factor log N of ideal minimum risk.
A good choice for threshold *thr* is as shown in equation (13)

$$thr = \sigma_n \sqrt{NlogN} \qquad (13)$$

where σ_n is standard deviation of noise and N is number of wavelet coefficients. A robust estimation of σ_n has been used, calculated from detail wavelet coefficients of an additional decomposition of x as shown in equation (14)

$$\widehat{\sigma_n} = median(|d_I|)/0.6745 \qquad (14)$$

Denoising scheme confirms that decomposition at level 1contains "pure" noise, and should be killed. Notice that the sampling interval was 30 micrometre, and if the same decomposition would have been applied to the images sampled in 100 micrometre resolution, level 1 decomposition would contain signal information as well. Applied to other levels, denoising enhances the reconstructed images, especially in higher frequency sub-bands (level 2 and 3). The entire algorithm is illustrated in Figure 6.

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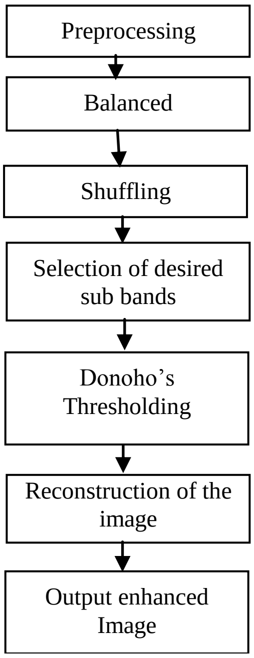

Fig 5. Flow chart for the proposed method of Mammogram enhancement

VI. RESULTS AND INFERENCES

Balanced multiwavelets with Donoho's thresholding for Image Enhancement

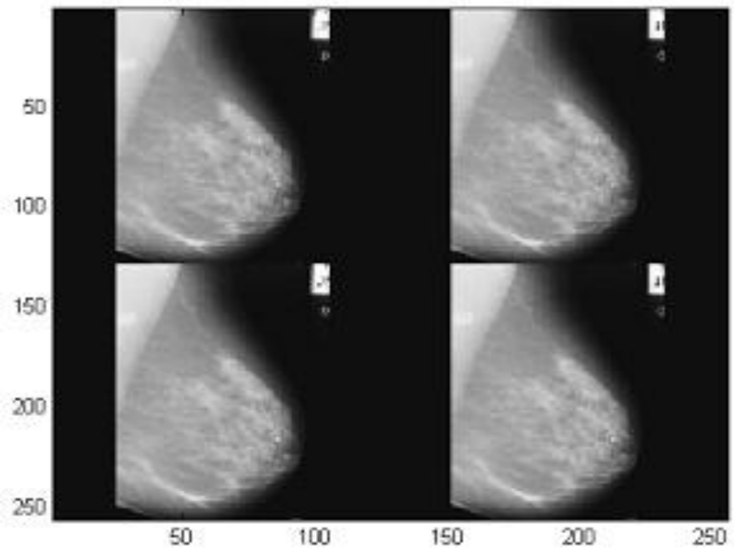

Fig 6. Unbalanced preprocessed Image

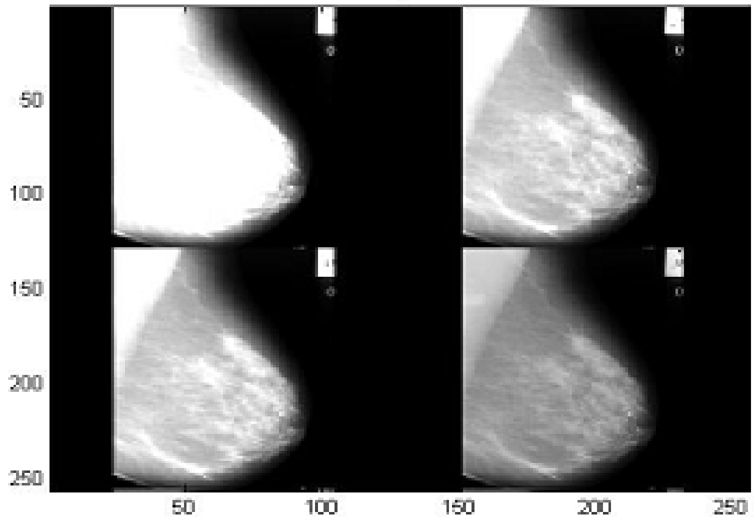

Fig 7. Balanced preprocessed Image

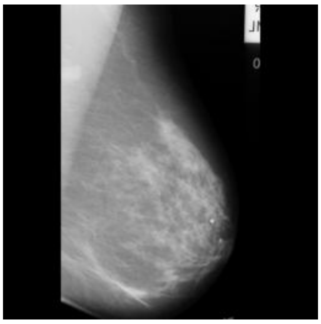

Fig 8. Balanced Recovered Image

Figure 6 and Figure 7 show the result of unbalanced processed image and balanced processed image using balanced multiwavelets with Donoho's thresholding before recovery. Figure 8. Shows the balanced recovered image where microcalcfication is seen as a bright white spot.

Table 1 Mean Ranks of the Original and Four Enhanced Images Showing Micro calcifications

Observer	Original	Type of Image Enhancement Algorithm (Numbers in parentheses represent number of cases in which each algorithm was assigned the highest preference)			
		Adaptive unsharp masking	CLAHE	Wavelet based enhancement	Multi-wavelet based enhancement
Observer 1 Malignant (n = 10)	2.7 (0)	3.2 (1)	4.5 (0)	1.8 (4)	1.7 (6)
Observer 2 Malignant (n = 10)	3.0 (1)	3.2 (1)	4.9 (0)	2.7 (3)	2.3 (5)
Observer 3 Malignant (n = 10)	2.8 (1)	2.5 (1)	5.0 (0)	2.0 (6)	1.7 (4)
All Observers Malignant (n = 30)	2.8(2)	3.0(3)	4.8(0)	2.2(13)	1.9(15)

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VII. CONCLUSION

The average rank of the original and four enhanced images for malignant micro calcifications for each of the Three observers physician is given in Table 1. A low score indicates that a high preference. In parentheses it is indicated that the number of cases in which each algorithm was assigned the highest preference (i.e., a score of 1). The bottom of the table gives the average rank and the number of cases in which each algorithm was ranked the best in parentheses, for 30 interpretations (10 cases x 3 observers) for malignant lesions. For micro calcifications, the multiwavelet based image enhancement had the lowest average ranking overall (highest preference) followed by the wavelet based image enhancement algorithm. Of the 30 interpretations (10 cases x 3 observers), the multiwavelet algorithm was chosen as the most preferred in 50% (15/30) of the interpretations, the wavelet based image enhancement in 43.3% (13/30). The visual observation is better in multiwavelet based enhanced images than the existing algorithms like adaptive unsharp masking, contrast limited adaptive histogram equalization and wavelet based algorithms.

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