# DETECTION OF MICROCALCIFICATION IN DIGITAL MAMMOGRAMS USING ONE DIMENSIONAL WAVELET TRANSFORM

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*Abstract*
*Mammography is the most efficient method for breast cancer early detection. Clusters of microcalcifications are the early sign of breast cancer and their detection is the key to improve prognosis of breast cancer. Microcalcifications appear in mammogram image as tiny localized granular points, which is often difficult to detect by naked eye because of their small size. Automatic and accurately detection of microcalcifications has received much more attention from radiologists and physician. An efficient method for automatic detection of clustered microcalcifications in digitized mammograms is the use of Computer Aided Diagnosis (CAD) systems. This paper presents a one dimensional wavelet-based multiscale products scheme for microcalcification detection in mammogram images. The detection of microcalcifications were achieved by decomposing the each line of mammograms by 1D wavelet transform into different frequency sub-bands, suppressing the low-frequency subband, and finally reconstructing the mammogram from the subbands containing only significant high frequencies features. The significant features are obtained by multiscale products. Preliminary results indicate that the proposed scheme is better in suppressing the background and detecting the microcalcification clusters than any other wavelet decomposition methods.*

*Keywords:*
*Computer Aided Diagnosis (CAD), One Dimensional Wavelet Transform, Multiscale Product, Microcalcification Detection*

## 1. INTRODUCTION

Today, Breast cancer is the frequent type of cancer among women and comprises the second leading cause of mortality in women after lung cancer. It is a disease in which cells in the tissues of the breast become abnormal. These abnormal cells become a tumor. According to WHO report, more than 150000 women die of breast cancer every year worldwide. Primary prevention seems impossible since the causes of this disease are still remaining unidentified. Thus, early detection is the key to improve breast cancer prognosis. There is clear confirmation which shows that early detection and treatment of breast cancer can increase the survival rate. The earlier stage of the breast cancer is detected, the chance that a proper treatment can be prescribed. The analysis of X-ray mammograms is an important preventive care for early diagnosis of breast cancer. Microcalcification clusters are one of the important early sign of breast cancer [1].

Microcalcifications are quite very tiny bits of calcium deposits present in the breast regions. It shows up as clusters or in patterns in mammograms and it appear as nodular points with high brightness, small localized granular points along the breast,

whereas normal tissues such as mammary ducts and blood vessels are linear in structure [2]. However, detection of the microcalcification clusters in the X-ray mammograms is a major challenge to radiologists because surrounding dense breast tissue makes suspicious areas almost invisible. Also some of Microcalcification clusters are not detected by radiologists due to its small size and nonpalpable [3]- [4]. To avoid these problems, a Computer Aided Diagnosis (CAD) system has to be developed. The computer output is presented to radiologists as a "second opinion" and that improves the accuracy in the detection progress.

Numerous methods have been proposed for Microcalcification detection. These are based on suppressing background information and amplifying the abnormal areas.

Examples for these methods include Chan et al. [5], [6] developed a computerized scheme based on a difference image technique, Yoshida et al. [7], [8] used a discrete wavelet transform(DWT), Laine et al. [9], [10] applied dyadic wavelet decompositions, Wang and Karayianis [11] presented an method employing wavelet-based subband image decomposition for detecting microcalcifications in digital mammograms. D.Sersic et al [12] introduce a novel filter bank based on redundant wavelet transform and Chun-Ming Chan et al [13] developed an enhancement method relying on multiscale wavelet analysis. Some of these methods are based on 2-D wavelet transform decomposition. In this paper, we have proposed the method one dimensional singularity detection based on multiscale products. This method gives better results for the detection of microcalcifications in mammograms.

The rest of the paper is organized as follows: section II presents wavelet analysis and the proposed method with multiscale product analysis in section III; Experimental results obtained on execution of method are presented in section IV and conclusion as the last section.

## 2. WAVELET ANALYSIS

Wavelets are a mathematical tool for hierarchically decomposing the signal in the frequency domain by preserving the spatial domain. Wavelet transform provides an alternative to more traditional {Fourier transforms} used for analyzing the signals and images. It has advantages over Fourier methods in analyzing physical situations where the signal contains singularities and discontinuities [14]. Since wavelet introduction, it has found more and more applications such as signal denoising and feature detection [15]. Using wavelets, a signal pyramid can

be produced which represents the entropy levels for each frequency. In this paper, we demonstrate how this property can be exploited to detect microcalcification in mammogram images based on their frequency response in various frequency bands.

The basic idea of wavelet transformation is to represent any arbitrary function as a superposition of a wavelet basis [16], [17]. The coefficients of the basis can be used to reconstruct the original function exactly. The wavelet basis is formed by dilation and translation of a special function, which is called the mother wavelet. The wavelet transform gives a spatial and frequency representation of signals.

As the discrete wavelet transform corresponds to basis decomposition, it provides a non-redundant and unique representation of the signal. These fundamental properties are key to the efficient decomposition of the non-stationary processes typical of Mammogram experimental settings. Consequently, wavelets have received a large recognition in biomedical signal and image processing.

The One –dimensional signal is considered, which can be easily extended to multiple dimensions. An orthogonal wavelet transform is characterized by two continuously-defined scaling function $\Phi(x)$ and its associated wavelet function $\Psi(x)$. The wavelet basis functions are constructed by dyadic dilation (index j) and translation (index k) of the mother wavelet

$$\Psi_{j,k} = 2^{j/2}\Psi(2^j x - k) \tag{1}$$

where $\Phi(x)$ and $\Psi(x)$ can constitutes an orthonormal basis of $L^2(R)$, which is the space of finite energy functions. This orthogonality permits the wavelet coefficients $d(j,k)$ and approximation coefficients $c(j,k)$ of any function $f(x) \varepsilon L^2(R)$ to be obtained by inner product with the corresponding basis functions

$$d(j,k) = \langle f, \Psi_{j,k} \rangle \tag{2}$$

$$c(j,k) = \langle f, \phi_{j,k} \rangle \tag{3}$$

where $\langle f, g \rangle = \int f(x)g(x)dx$ is the conventional $L^2(R)$ inner product. In practice, the decomposition is only carried out over a finite number of scales J. The wavelet transform with a depth J is then given by

$$f(x) = \sum_{k \varepsilon Z} d(j,k)\Psi_{j,k} + \sum_{k \varepsilon Z} c(j,k)\phi_{j,k} \tag{4}$$

Although the synthesis and e*xp*ansion formulas (2) and (3) are given for continuous signals, there exists an equivalent expression for a purely discrete framework.
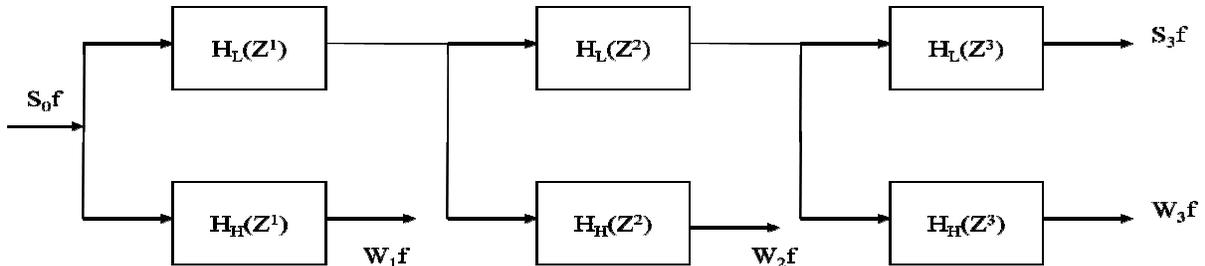
Fig. 1 shows the analysis bank and synthesis bank of the filter bank for one dimensional discrete wavelet transform. Downsampling operator in analysis bank removes the odd samples after filtering and upsampling operator in synthesis bank inserts a zero in-between the samples before filtering. Low-pass output is iterated at each scale in the two-channel filter bank.
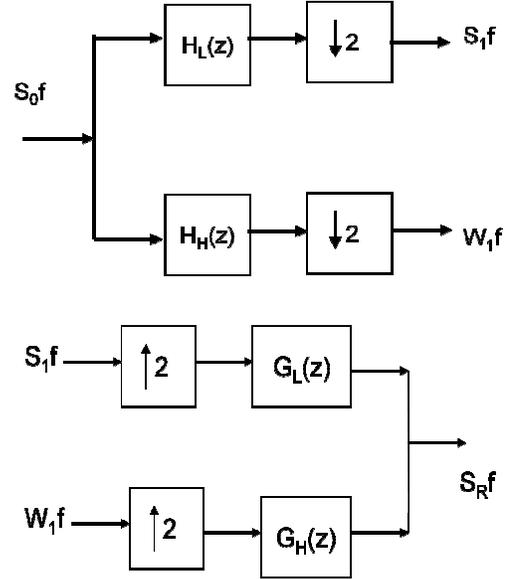


Fig.1. One dimensional filter bank

where $S_0f$ is input signal and $S_Rf$ is reconstructed signal. $S_1f$ and $W_1f$ correspond to the low pass and high pass output signal by applying wavelet transform. $H_L(Z)$ and $G_L(Z)$ is the low pass filter of analysis and synthesis bank, $H_H(Z)$ and $G_H(Z)$ is the high pass filter of analysis and synthesis bank. However, maximally decimated filter bank is not always useful for signal analysis, because significant details are decimated by the downsampling[8]. Therefore, the filter bank without sampling operators is employed. Fig. 2 shows the DWT without sampling operator at scales from 1 to 3. The filter bank for 1D-DWT is usually given by iterating the low-pass channel of the two-channel filter bank. In each level 2j is used for the order of Z at scale j. Length of the signal is same in all scales. If input signal $S_0f$ has 100 samples, then at each scale coefficients $S_jf$ and $W_jf$ also have 100 samples.
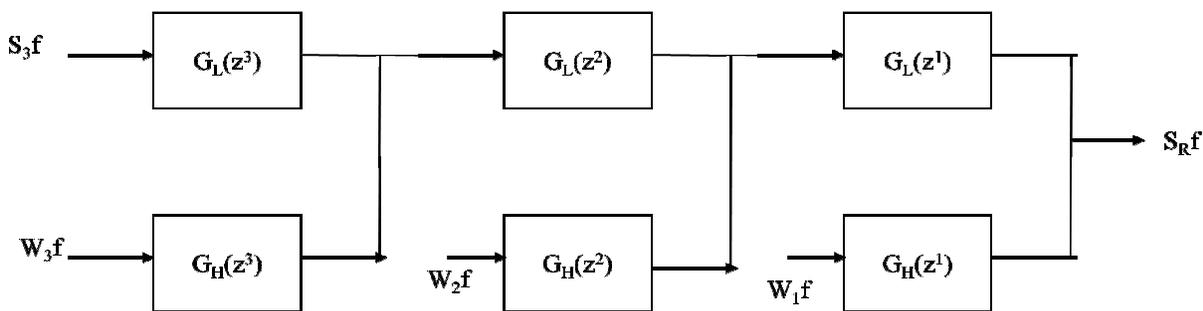


Fig 2. (a) 1-D DWT analysis bank

Fig 2. (b) 1-D DWT analysis bank

## 3. PROPOSED METHOD WITH MULTISCALE ANALYSIS

Microcalcifications appear as group of tiny granular bright spots. These bright spots are high frequency in nature. So it can be extracted by using wavelet based subband decomposition.

Microcalcification can be detected by describing the high peak values in the detail plane of multiresolution scheme. One dimensional discrete wavelet transform are applied on each line of mammogram image. Different wavelet families with different null moments have been applied. Instead of this, we preferred coiflet or biorthognal wavelet transform, which gives very low values in the normal regions and high Peak values at abnormal regions [18].

It is complicated to pick up the significant features from details coefficients, because significant coefficients are mixed with non-significant adjacent coefficients [19]. To overcome this, we present multi-scale product scheme to incorporate the merits of interscale dependencies for microcalcification detection. The two adjacent wavelet detail coefficients are multiplied to amplify the significant features and reduce the insignificant background features [20] [21].

Fig. 3 shows a single row on mammogram image which contains microcalcification. A sharp Peak indicates microcalcification region and other samples indicates background region
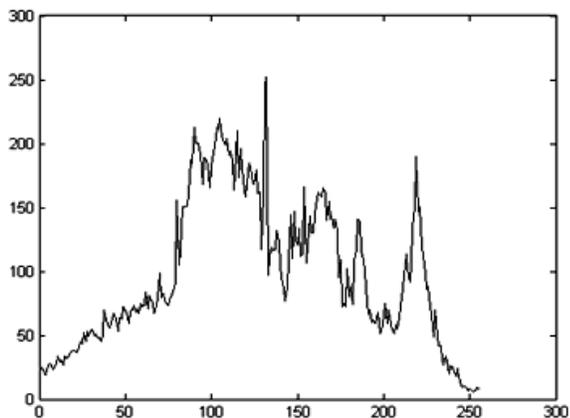
Fig.3. Microcalcification profile along horizontal direction

One dimensional multiresolution wavelet transform was applied on this profile up to four levels. Fig 4, the DWT at the

first four scales of a microcalcification profile are shown. Notice that the singularities in images have high magnitude value across scales while non-specific background has low values. It is difficult to extract these singularities from the detail planes because of singularities are surrounded by insignificant neighborhood wavelet coefficients.To avoid this problem, multi-scale products are used at adjacent scales. In the Multiscale products, singularities can be efficiently distinguished from non-relevant ones. Multiscale products are calculated by multiplying adjacent wavelet scale coefficients. These products are used to increase the magnitude of the singularities and to weaken the homogeneous region [22]. Fig. 5 shows multiscale product of wavelet coefficients at adjacent scales. Indeed, it is easy to extract the singularity (microcalcification) from the Mammogram.

For 1D-DWT, multiscale products of wavelet coefficients are calculated by

$$P_m = \prod_m^{m+1} W_m \qquad (5)$$

where $P_m$ is multiscale product at scale $m$. $W_m$ and $W_{m+1}$ is adjacent wavelet coefficients of scale $m$. So Multiscale product are obtained to a scale varies upto four is given as
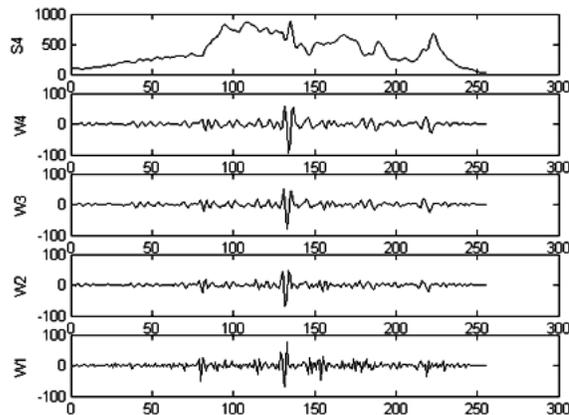
$$P_m = W_m \cdot W_{m+1} \qquad (6)$$

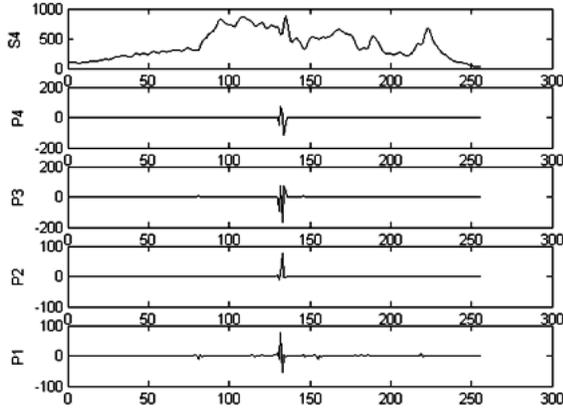Fig.4. Decomposition of Microcalcification profile

Fig.5. Multiscale products of wavelet coefficients

The steps of proposed method are as follows. At first, one dimensional discrete wavelet transform are applied on each line of mammogram at both horizontal and vertical direction separately upto 4 scales. The Multiscale products are calculated and thresholding is applied before reconstruction. The wavelet coefficients is threshold by

$$W_j^X = \begin{cases} g \cdot W_j^X & ; \text{if } P_j^X \geq \lambda \cdot \text{Max}(P_j^X) \\ 0 & ; \text{if } P_j^X < \lambda \cdot \text{Max}(P_j^X) \end{cases} \quad (7)$$

where $\lambda$ is any positive constant, which is to be obtained after some trial run. The detection of the microcalcification is best for the $\lambda$ value in the range of 0.1 to 0.3. Determination of threshold value is extremely important for microcalcification detection. $\text{Max}(P_j^X)$ is the maximum value of multiscale product at each subband. Where X is the variable used to indicate the horizontal and vertical Directions. The detail coefficients of all scales, which have value less than threshold, are set to zero. Finally to extract the microcalcification clusters from the original size of the reconstruction weighted higher frequency subbands, the coarsest approximation coefficients are set to zero. The above proposed method was applied to each line of mammogram image both in horizontal and vertical direction. Microcalcification detected image was obtained by combining both resultant horizontal and vertical image.

## 4. EXPERIMENTAL RESULTS

The proposed method was implemented in MATLAB 7.0 and verified on the set of mammogram image with different size and features which were obtained from DDSM database. Mammograms were digitized to a pixel size of 0.0435 mm x 0.0435 mm and gray level depths are 12bits. To claim the results obtained from the proposed method to be superior, a comparison was made with 2-D wavelet transform decomposition and threshold by OTSU method.

Fig.6(a) shows a Original mammogram image of size 512x512. Fig.6(b) shows the horizontal detected image by applying proposed one dimensional wavelet transform on each row of the image. Fig.6(c) shows the Vertical detected image by applying proposed method on each column of the image. Fig.6(d) shows the Combined resultant image. The output of the

proposed method clearly gives an area of microcalcification presence in the mammogram without any overshoot in the detail regions
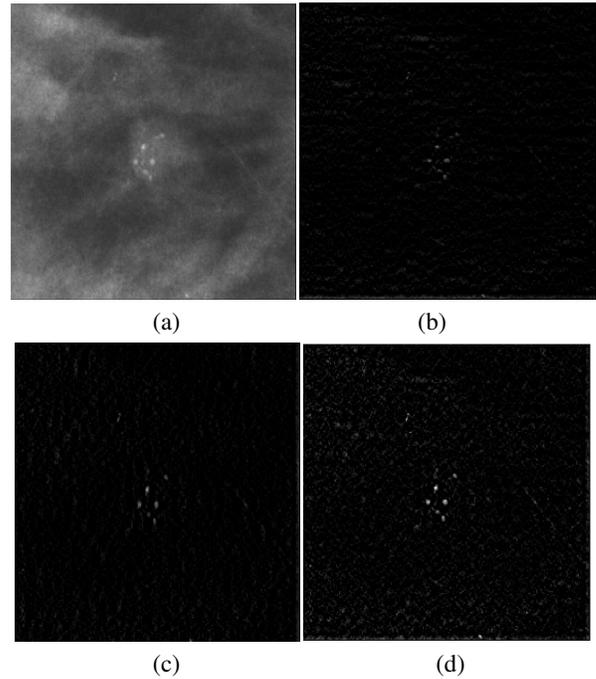


(a)　　　　　　　(b)



(c)　　　　　　　(d)

Fig 6 a) Original image b) Horizontal detected image c) Vertical detected image d) Combined output



(a)　　　　　　　(b)



(c)　　　　　　　(d)

Fig.7 (a) Part of Original mammogram image b) Detection by OTSU threshold method c) Detection by 2-D wavelet decomposition d) Detection by Proposed method

<table>
<tr><td>(a)</td><td>(b)</td></tr>
<tr><td>(c)</td><td>(d)</td></tr>
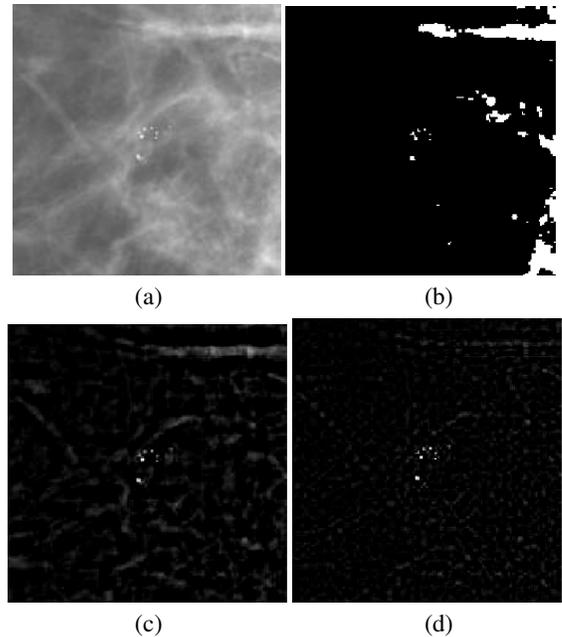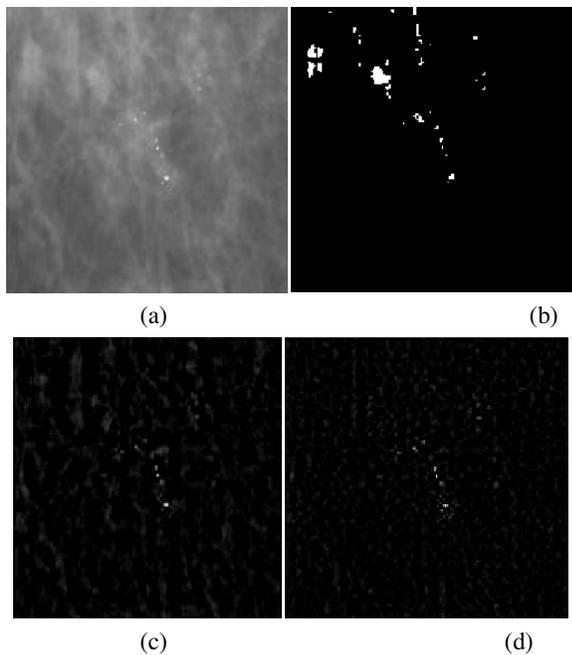</table>

Fig 8 a) Part of Original mammogram image b) Detection by OTSU threshold method c) Detection by 2-D wavelet decomposition d) Detection by Proposed method

Fig.7 (a) shows a low contrast mammogram image and Fig.7(b) shows resultant image using universal OTSU threshold method. Fig.7(c) shows the microcalcification detected image by 2-D decomposition in wavelet domain and Fig.7(d) shows the detected image by proposed method respectively. Resultant images by proposed method clearly show the calcification present in the mammogram. Detected image by proposed method shows that it suppressed non-significant background information, where 2-D wavelet decomposition and OTSU threshold method introduces artifacts. Fig.8. represents the results obtained using proposed method for another case of mammography.

We used to evaluate the performance of Microcalcification detection is the free-response receiver operating characteristic (FROC) curve [23]. It is a plot of the true-positive detection ratio (TP) versus the average number of false positives (FPs). True positive detection ratio here refers that how many true microcalcifications are correctly detected by computerized scheme and false positive per image refers to how many true microcalcifications are missed.It is clear that proposed method have higher TP ratio compared with 2D wavelet transform. From Fig.9, the proposed method has the TP ratio of 91.3% for a 1.5 FP/image and the 2D wavelet method has the TP ratio is 90.8% for a 1.5 FP/image. The detection capability of the one dimensional wavelet transform combined with multi scale is much higher than the two dimensional wavelet methods. The resultant image obtained by the proposed method clearly identifies a cluster of microcalcification in the mammogram without any overshoot in the detail regions. This method limits the emphasis of details when they are already very well defined in order to avoid the generation of annoying artifacts.
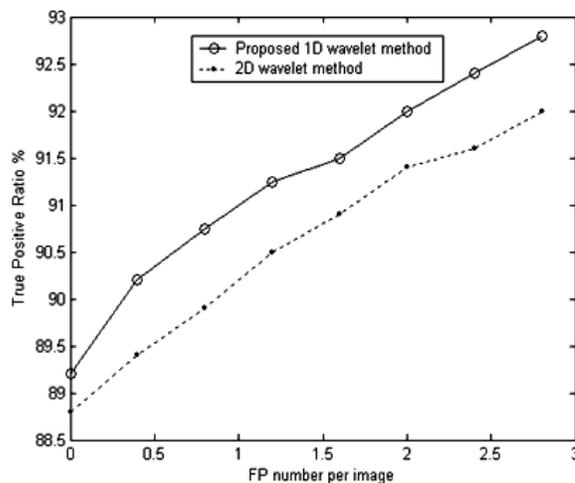


Fig.9. FROC Curve of Microcalcification Detection

## 5. CONCLUSION

In this paper, the development of a CAD system for the automatic detection of microcalcification clusters in mammogram was presented. Microcalcification cluster detection based on 2D wavelet decomposition is used in many works before. In this paper, one dimensional DWT with multiscale analysis was proposed. The proposed CAD system consists of three steps. In the first step, one dimensional discrete wavelet transform was applied on each row (horizontal) and column (vertical) of mammogram separately up to 4 scales. In second step, multiscale products are calculated and significant features are effectively distinguished from background. On reconstruction, higher frequency subbands was enhanced with local gain and lowest frequency subband was suppressed. This approach enhances the image significant features associated to malignancies, thus allowing image interpretation. In third step, the Final detected image was obtained by combining the horizontal and vertical image. The detection result obtained by the proposed method seems to be the most suitable, since it extracts the location of microcalcifications. The computational complexity of the proposed algorithm is high compared to 2D wavelet transform. But the results were promising that this method could detect the microcalcifications accurately than 2D wavelet transform. The proposed algorithm was tested on both normal and abnormal images. We tested 100 images taken from DDSM mammogram database. Based on the results, the proposed method detects the microcalcifications up to 96% accuracy. In the future, we aim to apply our method to compute the size of each microcalcification by introducing the shape information of microcalcification into the multiresolution analysis.

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