Wavelets Study for better multiresolution analysis in CAD of Microcalcification

Nizar Ben Hamad[1], Atef Masmoudi[2] and Khaled Taouil[3]

[1] SETIT, ISBS, University of Sfax
Sfax, BP:261-3000, Tunisia

[2] SETIT, ISBS, University of Sfax
Sfax, BP:261-3000, Tunisia

[3] ISECS-University of Sfax
Sfax, BP 868-3018 Tunisia

Abstract

Wavelets have enjoyed a widespread exposure in applications of image processing and computer vision. So mush so that wavelet is widely used in medical applications as the computer aided detection of microcalcifications in mammograms. A several types of wavelet transforms were employed in algorithms to achieve automated detection of microcalcifications. In this work we present a comparative study of wavelets to pick the better one and its optimal potential level of decomposition that give us better detection. Our algorithm involves four steps: First, delimitation of the Region of Interest. Second, extraction of microcalcifications profiles. Next, a 1-D DWT with different families of wavelet is applied on the signal up to the sixth level. Finally, comparison between details coefficients of each level is done to carry out the optimal level. To prove our result, 2-D wavelet transform decomposition and reconstruction with the list of wavelets used above and up to the optimal level of each one is applied on digital mammograms from the MIAS data base (Mini Database for Screening Mammography) to carry out microcalcifications. A comparative study based on the true positive (TP) is performed to confirm the result.

Keywords: Multiresolution approach, 1-D Discrete Wavelet Transform, Breast cancer, Microcalcification.

1. Introduction:

Mammography is effectively the widely used imaging modality for breast cancer screening. Mammograms are the most difficult of radiological images to interpret since they are of low contrast. Also, features in mammograms indicative of breast disease, such as microcalcifications, are often very small. Therefore, a computer system has been already used to help the radiologists to pre-screen mammograms.

Considerable research, last twenty years, has been undertaken in the development of automated detection of microcalcifications. Several image processing methods were proposed (a thorough review of various methods can be found in Thangavel et al. [1]. Among these, there are many promising wavelet approaches based on the discrete wavelet transform multiresolution analysis.

Although, there are various wavelet decomposition approaches microcalcifications detection algorithms, the study of the optimal level of decomposition is of great interest to perform computer aided detection of microcalcifications based on multiresolution wavelet transform.

The remainder of the paper is organized as follows. First, some wavelet-based approaches are presented in section II. Next, we introduce a brief overview of wavelet transform and multiresolution approach in Section III. The proposed approach is developed in Section IV. Results and applications are presented in Section V. Finally, conclusion and some proposes directions for future work are given in Section VI.

2. Overview of some wavelet-based approaches

A several types of wavelet transforms were employed in algorithms to achieve automated detection of microcalcifications. In this section, a few most important techniques for microcalcification detection are reviewed.

M.G. Mini et al[2] present two novel WT-based schemes for the automatic detection of clustered microcalcifications in digitized mammograms. The proposed algorithms achieve high detection efficiency and low processing memory requirements. The detection is achieved from the parent–child relationship between the zero-crossings [Marr-Hildreth (M-H) detector] /local extrema (Canny detector) of the WT coefficients at different levels of decomposition. The Biorthogonal wavelet “bior 1.3” of support 6 for edge detection was used at the third level decomposition.

M. Rizzi et al in [3] introduce a new procedure based on preserving suspect microcalcifications and reducing background noise by thresholding mammograms through a wavelet filter, according to image statistical parameters on the one hand. On the other hand, the reconstructed image is decomposed adopting another wavelet and each decomposition level is processed using a hard threshold technique in order to localize singularity points.

Wang and Karayianis [4] presented an approach for detecting microcalcifications in digital mammograms employing wavelet-based subband image decomposition. Given that the microcalcifications correspond to high-frequency components of the image spectrum, microcalcifications can be extracted form the original mammograms by suppressing the subband of the wavelet-decomposed image that carries the lowest frequencies, before the reconstruction of the image.

M. Al-Qdah et al [5] use the db4 wavelet to detect microcalcifications in mammogram-digitized images obtained from Malaysian women sample. The wavelet filter's detection evaluation was done by expert radiologist. An evaluation system is designed to evaluate the findings of the radiologist over some period of cancer detection working time.

S.Sentelle et al [6] shows that a multiresolution FCM-based segmentation combined with wavelet processing can be employed to quickly detect and segment calcifications as a possible pre-processing step for a classifier. This algorithm exhibits difficulty with the detection of some subtle calcifications. Overall, it is expected that the addition of linear structure detections, fined tuned fuzzy rules, local measurement of standard deviation and enhanced use of the FCM algorithm output during the pre-processing stage could result in significant improvements in performance.

P.Heinlein et al [7] presented a new algorithm for enhancement of microcalcifications in mammograms. The main novelty was the application of techniques developed for construction of filterbanks derived from the continuous wavelet transform. These discrete wavelet decompositions, called integrated wavelets, are optimally designed for enhancement of multiscale structures in images. These techniques were applied to the detection of microcalcifications. The algorithm was positively evaluated in a clinical study. It has been implemented in a mammography workstation developed by IMAGETOOL.

Since microcalcifications appear as singularities in mammograms, G.Lemaur et al [8] provide new wavelets with a higher Sobolev regularity compared the classical wavelets, assuming the same support width. The results show that the detection of clustered calcifications in digitized mammograms is improved by the use of wavelets with a high Sobolev regularity.

V. Alorcon-Aquino et al [9] propose an approach to detect microcalcifications in digital mammograms using the dual-tree complex wavelet transform (DT-CWT).The approach follows four basic strategies, namely, image denoising band suppression, morphological transformation and inverse complex wavelet transform. Experimental results show that the proposed denoising algorithm and morphological transformation in combination with the DT-CWT procedure performs better than the stationary and discrete wavelet transforms and the top-hat filtering.

3. Wavelet transform and multiresolution approach

Because of a powerful underlying mathematical theory, wavelet methods of analysis and representation are presently having a significant impact on the science of medical imaging and the diagnosis of disease and screening protocols. They offer exciting opportunities for the design of new multiresolution image processing algorithms [10]. Wavelet transform give the both frequency and time information of the analyzed signal.

The interesting properties are as follows [11,12]:

Inversibility: We must be able to reconstruct an image from its discrete wavelet coefficients.

Admissibility: wavelet transform can be used for first analyze and then reconstruct a signal without loss of information.

Regularity: Wavelet regularity is a key property to improve the detection of singularities.

Translation covariance: Shifting the original image produce a wavelet coefficient shifting without changing its structure.

In this section, we describe the procedure of implementing the one-dimensional wavelet transform. Most signals correspond to waves which have high-frequency components of short duration (details) and low-frequency components of long duration (approximations) (Fig 1). Under these considerations, a multiresolution analysis works best with this kind of signals.

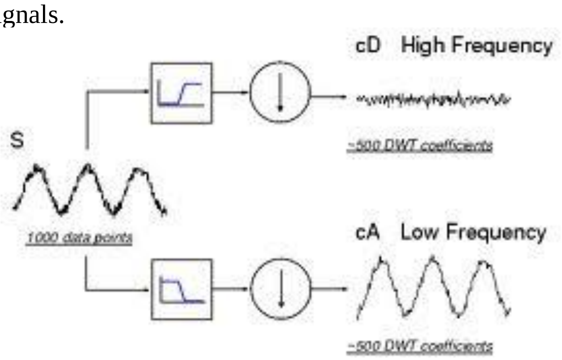


Fig. 1 Details and Approximation signals

3.1 1-D Wavelet analysis filter bank:

The 1-D wavelet transform analysis is the first step in the multiresolution approach.

Consider a multiresolution hierarchy with j levels. Each level contains an approximation, Aj, and details Dj. The original data can be thought of as A0. Approximation A1 is the low frequency components of A0, and D1 is the high frequency components of A0. The detail can be thought of as the difference between A1 and A0 so that A0=A1+D1=A2+D2+D1 etc…

Since the analysis process is iterative, in theory it can be continued indefinitely. In reality, the decomposition can proceed only until the individual details consist of a single observation.

The hierarchical model can be illustrated as follows (Fig.2):
The mathematical description of the multiresolution hierarchy follows:

$$a_0(t)=a_j(t)+\sum_{k=1}^{j}d_k(t) \quad (1)$$

$$a_j(t)=a_{j+1}(t)+d_{j+1}(t) \quad (2)$$

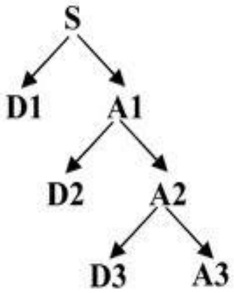


Fig. 2 Multiresolution Hierarchical Model.
S is the original signal.

Two closely related basic functions are needed for the multiresolution formulation. The first basic function is the wavelet function ψ(t) and the other basic function is called the scaling function and denoted by φ(t) [11]. All other wavelets are obtained by simple scaling and translating of ψ(t) as follows:

$$\psi_{a,\tau}=\frac{1}{\sqrt{a}}\psi(\frac{t-\tau}{a}) \quad (3)$$

In the most common formulation, the scaling is discrete and dyadic, a=2-j. The translation is discretized with respect to each scale by using τ=k2-jT. A one-dimensional orthonormal wavelet basis is generated from dyadic dilation and integer translation of the two basic functions, the ''father'' wavelet φ and the ''mother'' waveletψ.

$$\psi_{j,k}=2^{j/2}\psi(2^j t-kT) \quad (4)$$

$$\varphi_{j,k}=2^{j/2}\varphi(2^j t-kT) \quad (5)$$

The collection:

$$\{\varphi_{j0,k}\ 1\le k\le 2^{j_0}\}\cup\{\psi_{j,k}\ 1\le k\le 2^j,\ j\ge j_0\}$$

forms an orthonormal wavelet basis [13].
The two-parameter wavelet expansion for signal x(t) is given by the following decomposition series in which the scaling and wavelets functions are utilized.

$$x(t)=\sum_k c_k\varphi_{j_0,k}(t)+\sum_k\sum_{j=j_0}^{\infty}d_{j,k}\psi_{j,k}(t) \quad (6)$$

In this expansion, ck coefficients are referred to as approximation coefficients at scale j0. The set of dj,k coefficients represents details of the signal at different scales.

$$d_{j,k}=\langle x(t),\psi_{j,k}(t)\rangle=\int x(t)\psi_{j,k}(t)\,dt \quad (7)$$

$$c_k=\langle x(t),\varphi_{j_0,k}(t)\rangle=\int x(t)\varphi_{j_0,k}(t)\,dt \quad (8)$$

These coefficients can be find using discrete wavelet transform filter bank.
Mallat demonstrate that the dyadic nature of multiresolution approximations, in orthogonal basis, is closely related to the possibility of implementing the discrete wavelet transform (DWT) using filter bank. Further more, there is a recursive relation between cj and cj+1, also between dj and cj+1.
The procedure of implementation starts with passing this signal (sequence) x[n] through a half band digital lowpass filter with impulse response h[n]. Filtering a signal corresponds to the mathematical operation of convolution of the signal with the impulse response of the filter. The convolution operation in discrete time is defined as follows:

$$x[n]*h[n]=\sum_{k=-\infty}^{+\infty}x[k].h[n-k] \quad (9)$$

After passing the signal through a half band lowpass filter, half of the samples can be eliminated according to the Nyquist's rule. Simply discarding every other sample will subsample the signal by two, and the signal will then have half the number of points.
The DWT analyzes the signal at different frequency bands with different resolutions by decomposing the signal into a coarse approximation and detail information. DWT employs two sets of functions, called scaling functions φ(t) and wavelet functions ψ(t), which are associated with lowpass and highpass filters, respectively. The decomposition of the signal into different frequency bands is simply obtained by successive highpass and lowpass filtering of the time domain signal. The original signal x[n] is first passed through a halfband highpass filter g[n] and a lowpass filter h[n]. After the filtering, half of the samples can be eliminated according to the Nyquist's rule. The signal can therefore be subsampled by 2, simply by discarding every other sample. This constitutes one level of decomposition and can mathematically be expressed using the coefficients cj and dj as follows:

$$c_k^{j+1}=\sum_n c_k^j\,\tilde{h}[2k-n] \quad (10)$$

$$d_k^{j+1}=\sum_n c_k^j\,\tilde{g}[2k-n] \quad (11)$$

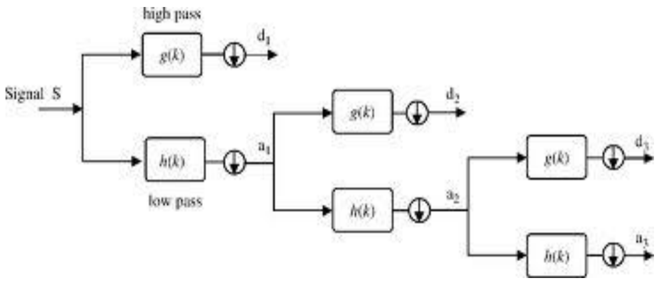
Where: $\tilde{h}[n]=h[-n]$ & $\tilde{g}[n]=g[-n]$

The above procedure, which is also known as the subband coding, can be repeated for further decomposition. At every level, the filtering and subsampling will result in half the number of samples (and hence half the time resolution) and half the highpass and lowpass filters are not independent of each other, and they are related by:

$$g[n]=(-1)^n h[1-n] \quad (12)$$

The implementation of the discrete wavelet transform using filter bank is showing in (Fig 3).
Since we require the transform to be orthogonal, the reconstruction of cj is done by computing the inverse using the transpose,

$$c_k^j = \sum_k ([d_k^{j+1} . g(2k-n)] + [c_k^{j+1} . h(2k-n)]) \quad (13)$$



↓ Down-sampling by 2.

Fig. 3 1-D DWT filter bank implementing

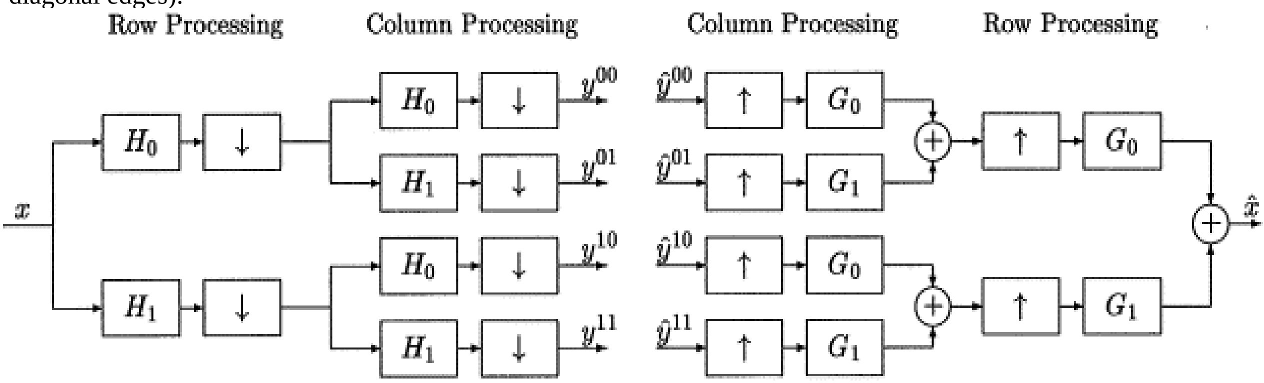
3.2 2-D Wavelet analysis and reconstruction filter bank:

For processing of images, the 1-D DWT is extended to 2-D DWT. Using tensor product wavelets, one performs the 1-D decomposition process along both x (row) and y (column) axes.
A total of four subband images HH(y11),HL(y10), LH(y01) and LL(y00) are generated (Fig 4). Different subband image contains different information and they may be processed individually using different algorithms. The subband image LL corresponds to the lowest frequencies. It contains the smooth information and the background intensity of the image. The subbands HL, LH, HH contain the detail information of the image. The subband HL gives the vertical high frequencies (horizontal edges), LH gives the horizontal high frequencies (vertical edges) and HH gives the high frequencies in both directions (corners and diagonal edges).

For reconstruction Filters, we denote the importance of choosing the right filters. In fact, the choice of filters not only determines whether perfect reconstruction is possible, it also determines the shape of the wavelet we use to perform the analysis.
The reconstruction can be performed from each level and each subimage while keeping the size of the reconstructed image the same as the original image.

4. Proposed approach

One of the important symptoms of breast cancer in the mammograms is the appearance of microcalcification clusters, which have a higher X-ray attenuation than the normal breast tissue and appear as group of small localized granular bright spots in the mammograms [14]. This bright spots, presented as singularities, appear in the frequency domain as high-frequency. It was denoted that high-frequency features of an image can be recovered locally using the wavelet-based subband decomposition
Different wavelet families are available and it is not always evident to decide the best wavelet to use for the detection of microcalcifications. Details coefficients with high modulus in the multiresolution scheme are associated to singularities. Therefore, the study of the potential level of subband decomposition is of great interest to perform computer aided detection of microcalcifications [15]. We propose the use of 1-D wavelet transform to find out this level.
Our algorithm consists of two main stages.
Stage 1: based on 1-D WT and composed of four steps: Dimension reduction of the image to reduce the dimensions of a data set. This work is performed by a cropping matlab function to delimitate the region of interest (ROI) which contain microcalcifications and a limit background area.
We perform a localization of microcalcifications according to notes of an expert radiologist. Then, we extract profiles of microcalcifications in two directions (vertical and horizontal).
1-D WT with different families of wavelet is applied on the signal up to the sixth level.



↓ Down-sampling by

↑ up-sampling by 2

Fig. 4 2-D DWT filter bank implementing analyze and reconstruction

Comparison between details coefficients of each level is done to carry out the better wavelet and its optimal level.
Stage 2: We perform 2-D wavelet decomposition up to this level+1. Then, details coefficients of all levels, which have modulus less then 50% of the maximum absolute value modulus of each level, are set to zero. This technique will decrease the rate of false detection due to noise, blood vessels and dense breast tissue in the mammograms. Finally, we reconstruct image, at the original size to preserve localization of microcalcifications, after putting the approximations coefficients of the last level at zero. A comparative study is performed using the positive predictive value PPV:

$$PPV = \frac{TP}{TP + FP} \quad (14)$$

The True Positive (TP) parameter means number of microcalcifications detected / number of microcalcifications proved by radiologist and the False Positive (FP) parameter means microcalcifications detected witch not proved to be microcalcification by radiologist [16].

5. Experimental results

The first step in stage 1 is the dimension reduction of the image to reduce the dimensions of a data set. (Fig 5). First we perform a cropping on the original image (1024X1024) then we extract the area including microcalcifications witch we call region of interest (ROI).

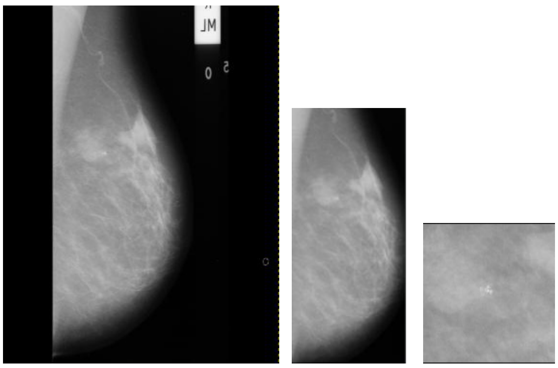


Fig 5. Original image, cropped image, ROI

The Second step in our algorithm is the extraction of microcalcification profile from digital mammograms into direction horizontal and vertical. (Fig 6 a,b).
More than 30 profiles have been extracted from 30 breast cancer mammograms enclosing microcalcifications. Next, 1-D multiresolution wavelet transform is applied until the sixth level.

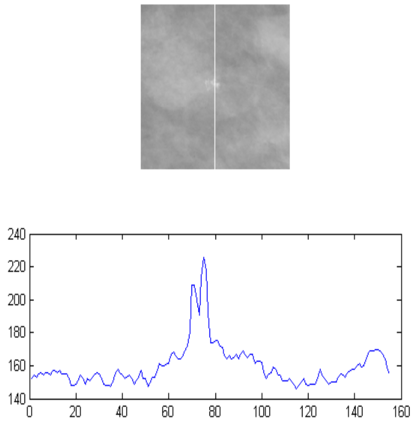


Fig. 6a vertical profile

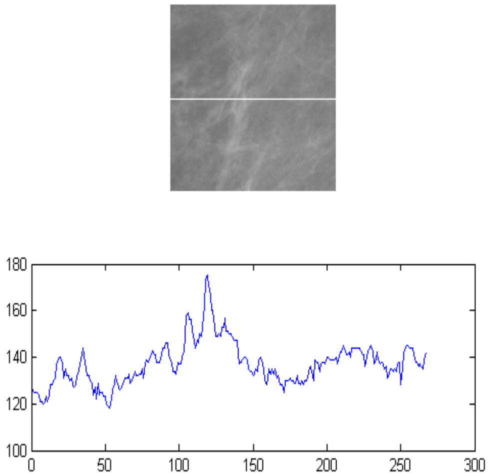


Fig. 6b horizontal profile

The result of the decomposition for profile of microcalcification in the horizontal direction is given in the graphics (Fig 7).
The graphics shows that the maximum details signal is obtained using the biorthogonal 2.2 wavelet and at the third level.

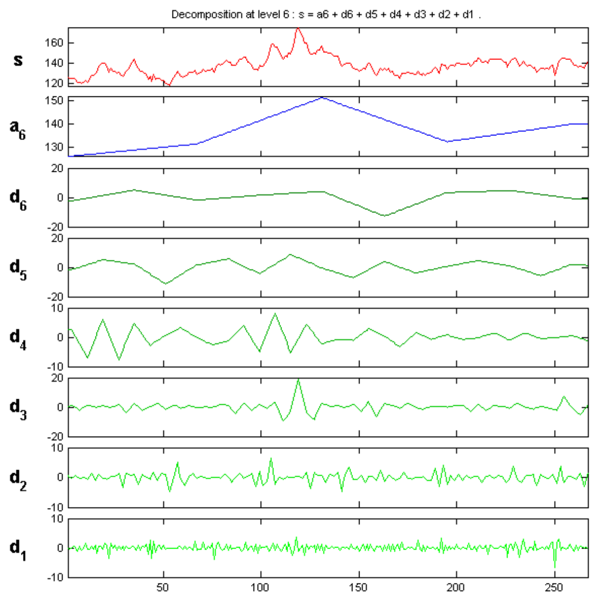


Fig. 7: 6th level decomposition with biorthogonal 2.2 wavelet; Profile along vertical direction.

Figure 8 shows, in the bottom, signal and approximation signal at level 1, in the middle, detail signal at level 3 and the last one shows details coefficients of all the 6th levels.

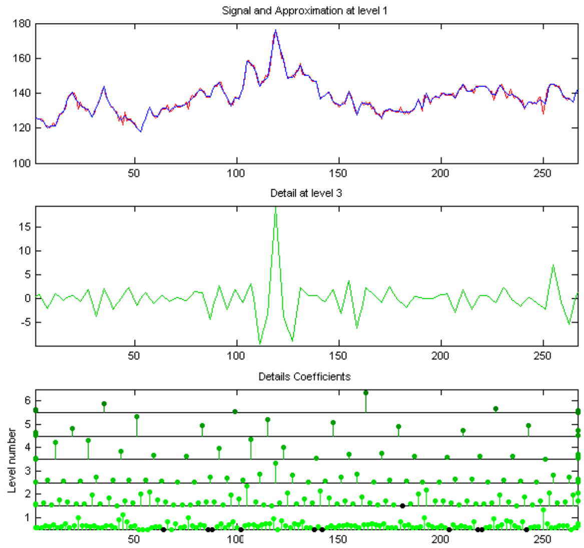


Fig. 8 : Detail signal at level 3

Our experiment is reproduced with the all 30 profiles. The result is given in (Fig9). In this graphic, sym2(4) means that we use the symlet 2 wavelet and the maximum detail coefficient for this wavelet is obtained at level 4.

From this graphic, it appears that wavelet function which resembles the shape of microcalcification profile provides higher details coefficients then others. However, we notice that for the same family of wavelets, the null moments of the wavelet act on the details coefficients modulus.

From (Fig 9) we denote that the Biorthogonal 2.2 wavelet gives the maximum details coefficient in the two directions at level 3.

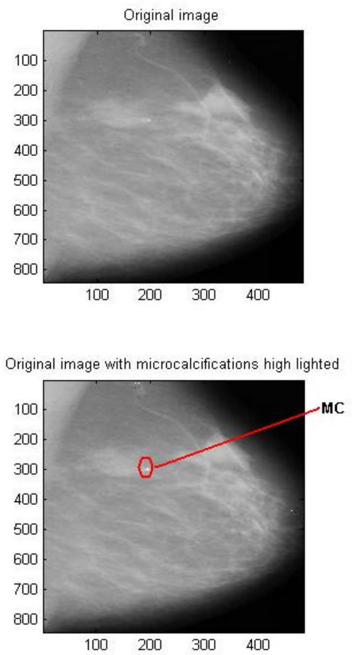


Fig. 10 : High lighted microcalcification

At the second stage of our approach, we perform 2-D wavelet decomposition up to the level 4 with all the wavelet families used in the first stage.

Fig 10 shows the original and the final image where microcalcifications are well high lighted after thresholding.

After reconstruction, we calculate the VPP relatives to each wavelet. The result is given in the table below (Tab1). From this table we denote that the Biorthogonal 2.2 wavelet gives the better PPV at all. This result confirms the one obtained in the first stage.

6. Conclusions

Detection of microcalcifications based on discrete wavelet subband image decomposition was used in many works before. In this paper, we have studied the optimal potential level of decomposition using the 1-D DWT with different families of wavelet. The results show that the optimal level is a function of the wavelet. More, the null moments of wavelets have a direct action on this optimal level. In fact, from certain number of wavelet null moments, profile of microcalcification will be mixed with the area behind.

The 2-D filter bank decomposition results show that the detection of clustered microcalcifications in digitized mammograms is improved by using wavelets which have functions similar to the profile shape of microcalcifications.

For further studies, it seems important to develop algorithms to find optimal level based on the relation between the properties of the wavelet function used for subband image decomposition and the modulus of details coefficients. Also, classifier algorithms will improve the false positive rate.

Table 1: Positive predictive value

images	*Wavelet families*	*Type*	*TP*	*FP*	*PPV*
30	Daubechie	2	27	7	79,41%
		3	26	7	78,79%
		4	26	7	78,79%
		5	25	9	73,53%
	Symlet	2	26	7	78,79%
		3	27	7	79,41%
		4	26	9	74,29%
		5	25	11	69,44%
	Coiflet	1	24	9	72,73%
		2	26	8	76,47%
		3	25	10	71,43%
		4	23	12	65,71%
		5	23	12	65,71%
	biorthogonal	2,2	29	6	82,86%
		2,4	27	8	77,14%
		3,5	25	10	71,43%

References

[1] K.Thangavel, M.Karnan, R.Sivakumar, A.Kaja Mohideen, "Automatic Detection of Microcalcifications in Mammograms- A Review", ICGST, 2005.

[2] M.G. Mini, M.Tech, V.P. Devassia, M.Tech, and Tessamma Thomas, "Multiplexed Wavelet Transform Technique for Detection of Microcalcification in Digitized Mammograms", Journal of Digit Imaging. 2004 December; 17(4): 285–291.

[3] Maria Rizzi, Matteo D'Aloia, Beniamino Castagnolo, "Computer aided detection of microcalcifications in digital mammograms adopting a wavelet decomposition", Integrated Computer-Aided Engineering Volume 16 Issue 2, April 2009 Pages 91-103

[4] Ted C. Wang and Nicolaos B. Karayiannis, "Detection of Microcalcifications in Digital Mammograms Using Wavelets", IEEE Tran. on Medical Imaging, vol. 17 pp. 498-509, Aug. 1998.

[5] Majdi Al-Qdah, Abd. Rahman Ramli and Rozi Mahmud, "A system of microcalcifications detection and evaluation of the radiologist: comparative study of the three main races in Malaysia, Computers in Biology and Medecine, vol 35 (2005) pp 905-914.

[6] S.Sentelle, C.Sentelle and M.A.Sutton, "Multiresolution-Based Segmentation of Calcifications for the Early Detection of Breast Cancer", Elsevier Science Ltd, Tran. on Real-Time Imaging, vol. 8, pp. 237-252 2002.

[7] Peter Heinlein, Johan Drexl and Wilfried Schneider, "Integrated Wavelets for Enhancement of Microcalcifications in Digital Mammograms", IEEE Tran. on Medical Imaging, vol. 22, n. 3, pp. 402-413 March 2003.

[8] G.Lemaur, K.Drouiche and J.DeConinck, "Highly Regular Wavelets for the Detection of Clustered Microcalcifications in Mammograms", IEEE Tran. on Medical Imaging, vol. 22, n. 3, pp. 393-401 March 2003.

[9] V. Alorcon-Aquino et al, "Detection of microcalcifications in digital mammograms using the dual-tree complex wavelet transform", Engineering Intelligent Systems, vol 17 no 1 March 2009.

[10] Michael Unser, Akram ALDROUBI and Andrew Laine "Wavelet in Medical Imaging", IEEE Tran. on Medical Imaging, vol. 22, n. 3, pp. 285-288 March 2003.

[11] Paul Sajda, Andrew Laine and Yehoshua Zeevi, "Multi-resolution and wavelet representations for identifying signatures of disease", IOS press, pp 339-363, 2002.

[12] M. Rafiqul Islam, "Wavelets, its Application and technique in signal and image processing", Global Journal of Computer Science and Technology, vol 11 Issue 4 Version 1.0 March 2011

[13] Ali. M.Reza, "Wavelet Characteristics", Lab UWM White paper, Oct. 1999.

[14] Songyang Yu and Ling Guan, "A CAD System for the Automatic Detection of Clustered Microcalcifications in Digitized Mammogram Film", IEEE Tran. on Medical Imaging, vol. 19, n. 2, pp. 115-126 February 2000.

[15] Marlin L. GENDRON and Dr. Juliette W. IOUP "Wavelet Multi-scale Edge detection for extraction of Geographic Features to Improve Vector Map Databases", Master dissertation, University of New Orleans Physics Department, vol. 53, pp.79-92.

[16] Nafiza Saidin "Segmentation of Breast Regions in Mammogram Based on Density: A Review", IJCSI International Journal of Computer Science Issues, Vol. 9, Issue 4, No 2, July 2012.

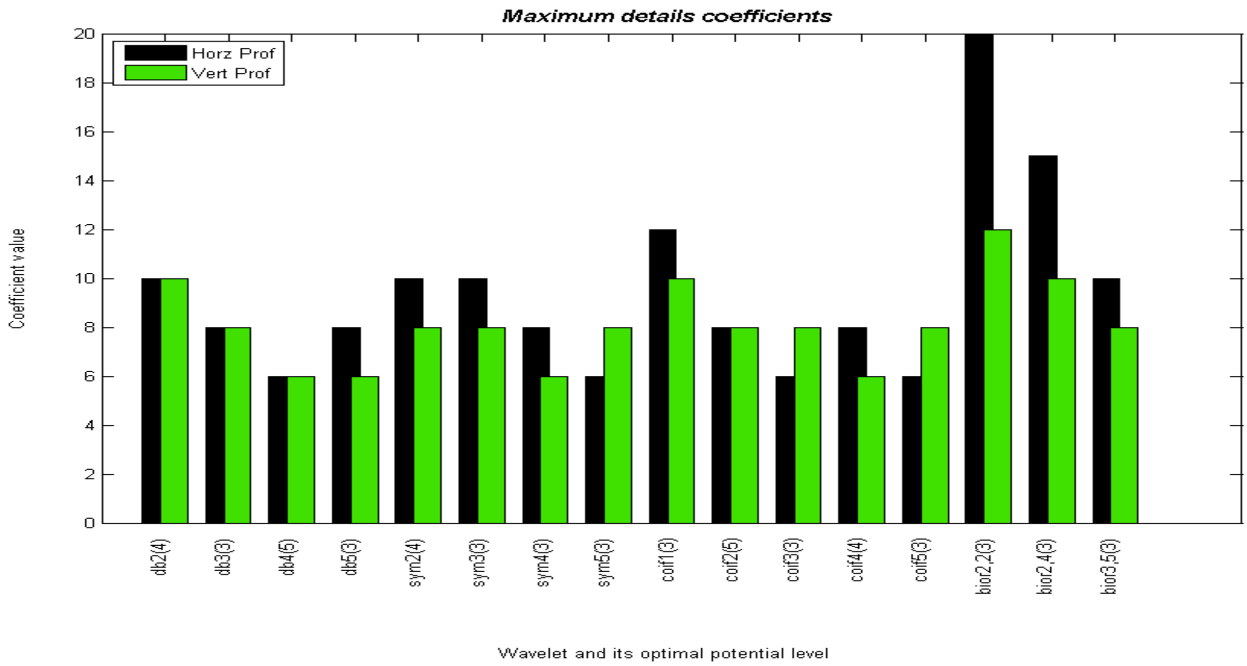


Fig. 9 : Maximum details coefficients