Microcalcification Detection using Multiresolution Analysis based on Wavelet Transform

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***Abstract*—Early detection is the key to improve prognosis of breast cancer, which is one of the most common forms of cancer among women. Currently, the most efficient method for breast cancer early detection is mammography. An early sign of 30–50% of breast cancer incidents is the appearance of clusters of fine, granular microcalcifications, whilst 60–80% of breast carcinomas reveal microcalcification clusters upon histological examination. An efficient method for automated classification of microcalcification clusters and thus for breast cancer control is the use of Computer Aided Diagnosis (CAD) systems. One of the most powerful computing methods these systems use is the multiresolution analysis of digitized mammographic images, based on wavelet transform. In this paper, we present a comparative study of such methods which are widely used in microcalcification detection and feature extraction. The detection of microcalcifications was achieved by decomposing the mammograms into different frequency sub-bands, and reconstructing the mammogram from the sub-bands containing only high frequencies, duo to the fact that microcalcifications correspond to high frequencies in the frequency domain of the image.**

I. Introduction

BREAST cancer is the most common type of cancer among women and comprises the second leading cause of cancer deaths for women today, after lung cancer. According to the World Health Organization, more than 1.2 million people will be diagnosed with breast cancer this year worldwide [1]. The American Cancer Society estimates that in 2005, approximately 211,240 women in the United States are expected to have been diagnosed with invasive breast cancer (Stages I-IV). Another 58,490 women are expected to have been diagnosed with in situ breast cancer, a very early stage of the disease [2]. Breast cancer is also the most common type of cancer in females in Europe. It is estimated that in the year 2004 there were 350,000 new breast cancer cases in Europe, while the number of deaths from breast cancer was estimated at 130,000. Breast cancer is responsible for 26.5% of all new cancer cases among women in Europe and 17.5% of cancer deaths [3].

Primary prevention seems impossible since the causes of this disease still remain unknown. Thus, early detection is the key to improve breast cancer prognosis. The only proven effective method of breast cancer early detection is mammography. There are some limitations, though, in human observing and it is difficult for radiologists to evaluate both accurately and uniformly the enormous number of mammograms generated in widespread screening. The presence of microcalcification clusters is an important sign for the detection of early breast carcinoma. High correlation between the appearance of the microcalcification clusters and the disease shows that CAD systems designed for automated detection of microcalcification clusters could be very useful and helpful for breast cancer control. A more extensive review on detection and classification methods of microcalcifications can be found in [4].

Although computer-aided mammography has been studied for over two decades, the mammographic image low contrast, the fuzzy nature of microcalcifications and the low ability of distinguishing them from their surroundings renders extremely difficult an automated characterization of microcalcifications. Major reasons for the above are:

a) the small size of microcalcifications, ranging between 0.1 and 1.0 mm, with an average value of about 0.3 mm. Actually some isolated ones are less than 0.1 mm and thus cannot be distinguished in the film-screen mammography due to high-frequency noise,

b) the huge variation in microcalcifications' size, shape and distribution which renders, simple template matching rather impossible,

c) the low contrast that microcalcifications may have, resulting in light intensity difference between suspicious areas and their surrounding tissues,

d) the fact that microcalcifications may be closely connected to surrounding tissues, in which case simple segmentation algorithms cannot work well.

e) the fact that in some dense tissues and/or skin thickening, especially in the breast of younger women, suspicious areas are almost invisible.

Wavelet theory comprises a powerful tool for multiresolution and texture analysis and it can be used very effectively for image processing. By using the multiresolution capability, the wavelet transform can separate small objects, such as microcalcifications, from

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large objects, such as large background structures.

Bazzani et al. [5] use the wavelet transform in order to detect structures having size smaller than 1mm by means of a multiresolution analysis. Borges et al. [6] apply wavelet transformation, using the Daubechies 4 and Haar wavelets, in image decomposition process and keep only the biggest in magnitude coefficients of the decomposed image in the first level of decomposition. Sentelle et al. [7] employ wavelet analysis to detect calcifications. This is done during wavelet processing by simply removing the lowest resolution approximation coefficients and performing a reverse wavelet transform. The reverse wavelet transform output is then thresholded appropriately to provide binary detections of calcifications. Soltanian-Zadeh et al. [8] use three different wavelet packets: Daubechies 6, 10 and 12 wavelets. Their method for feature extraction is based on image decomposition and then entropy and energy calculation in each of the sub-bands. They also apply multi-wavelet transformations with GHM, CL and SA4 multi-wavelets, using several scaling functions and mother wavelets. Lambrou et al. [9] use the Daubechies 4-TAP wavelet filter in all wavelet architectures. From all the signals and their wavelet transformation coefficients, they collect the first and second order statistical values, as well as the grey level run length measurements. Yoshida et al. [10], [11] apply wavelet transformation using the Least Asymmetric Daubechies' wavelets with length 8, 12 and 20 in order to enhance the microcalcifications. Finally, Ferreira et al. [12] evaluated a supervised classifier by transforming images in a wavelet basis, using the Haar and Daubechies 4 wavelets.

The purpose of this research work is to evaluate the different wavelets' families and determine the appropriate one for mammogram enhancement and microcalcification detection.

II. Materials and Methods

A. Wavelet Transform

The basic idea behind wavelet transform is to analyze different frequencies of a signal using different scales. High frequencies are analyzed using low scales whilst low frequencies are analyzed in high scales. This is a far more flexible approach than the Fourier transform, enabling analysis of both local and global features [13].

To be more specific, in wavelet transform, all of the basis functions, which are called wavelets, are derived from scaling and translation of a single function, called *mother wavelet*. Many types of mother wavelets and associated wavelets exist [14]. Depending on their properties, the wavelet transform can be divided into two categories, i.e., the *redundant* wavelet transform and the *orthogonal* wavelet transform. In this study, we use orthogonal wavelet transform, since it allows an input image to be decomposed into a set of independent coefficients, corresponding to each orthogonal basis. In other words, orthogonality implies that there is no redundancy in the information represented by the wavelet coefficients, which results in efficient representation and other desirable properties.

Each wavelet, ψ_{ab}, is defined by the scaling and translation of the mother wavelet ψ as follows:

$$\psi_{ab}(x) = \frac{1}{\sqrt{a}}\psi\left(\frac{x-b}{a}\right) \quad (1)$$

where a and b are integers representing scale (or level) and translation (or location), respectively. For certain mother functions, the set of wavelets ψ_{ab} forms a smooth, compactly supported (finite length), and orthogonal basis.

In order to define the wavelet transform we use the wavelets defined in (1) as basis functions, namely,

$$w_a^b = \frac{1}{\sqrt{a}}\int f(x)\psi\left(\frac{x-b}{a}\right)dx \quad (2)$$

where, w_a^b are the wavelet coefficients. The process utilizing this equation is called *wavelet decomposition* of the profile f(x) by means of the set of wavelets ψ_{ab}. In (2), each wavelet coefficient represents how well the profile f(x) matches with the wavelet with scale a and translation b. If the profile f(x) is similar to the wavelet at a particular scale and translation, then the coefficient has a large value. A wavelet coefficient, therefore, represents the degree of correlation or similarity between the profile and the mother wavelet at the particular scale and translation. Thus, the set of all wavelet coefficients w_a^b gives the wavelet domain representation of the profile f(x).

The basic approach for implementing the two-dimensional wavelet transform is the same as that used for the two-dimensional Fourier transform. First, the one-dimensional wavelet transform is applied to each row of an image and then the same transform is applied to each column. However, the one-dimensional wavelet transform is performed sequentially level by level. The two-dimensional wavelet transform can be implemented by applying the one-dimensional splitting algorithm to the horizontal and vertical lines (namely, rows and columns) of an image, successively.

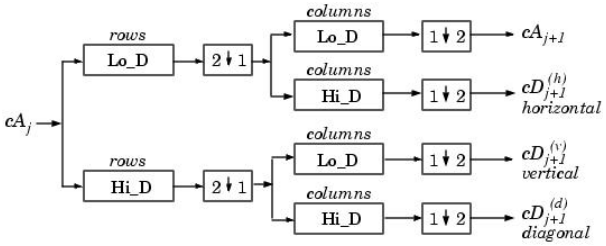

Fig. 1. Wavelet Decomposition of an image. Two-dimensional Wavelet Transform leads to a decomposition of approximation coefficients at level j in four components: the approximation at level j+1, and the details in three orientations (horizontal, vertical, and diagonal).

In Fig. 1 the two-dimensional wavelet transform is illustrated from level j to level j+1, where the wavelet representation at level j+1 consists of four sub-images. The first sub-image cA_{j+1} is obtained by applying the horizontal low-pass filter and the vertical low-pass filter successively. The second sub-image cD^{h}_{j+1} is obtained by applying the horizontal low-pass filter followed by the vertical high-pass filter. The third sub-image cD^{v}_{j+1} is obtained by applying the horizontal high-pass filter followed by the vertical low-pass filter. Finally, the fourth sub-image cD^{d}_{j+1} is obtained by applying the horizontal and vertical high-pass filters successively. The same process can be applied to every wavelet level.

B. Evaluation method

The evaluation of the wavelet transformations is based on the fact that the wavelet coefficients represent the degree of the similarity between the image and the mother wavelet. Thus, the assessment of the similarity is evaluated in each sub-band of the wavelet transform using the following equations:

$$Eh = 100\frac{\sum H^2}{\sum C^2} \quad (3)$$

$$Ev = 100\frac{\sum V^2}{\sum C^2} \quad (4)$$

$$Ed = 100\frac{\sum D^2}{\sum C^2} \quad (5)$$

where, H, V and D are the sub-arrays with the horizontal, vertical and diagonal detail coefficients respectively, and C is the array of the wavelet transform, containing the approximation as well as the horizontal, vertical and diagonal details.

Equations (3), (4) and (5) reveal the percentage of energy corresponding to the details of the wavelet transform. Due to the fact that the coefficients of the wavelet transform declare the degree of similarity, the appropriate wavelet function can be chosen by selecting the higher energy profile of the details.

C. Data Collection

The data used in our experiments were taken from the Mammography Image Analysis Society (MIAS). MIAS, which is an organization of research groups interested in the understanding of mammograms situated in UK, has produced a digital mammography database [15]. The X-ray films in the database have been carefully selected from the United Kingdom National Breast Screening Program and digitized with a Joyce-Lobel scanning microdensitometer to a resolution of 50 μm x 50 μm, with each pixel being encoded with 8 bits. The database contains left and right breast images from 161 patients. In total, it counts 322 images, belonging to three types, namely *normal*, *benign* and *malignant*. There are 208 normal, 63 benign and 51 malignant (abnormal) images.

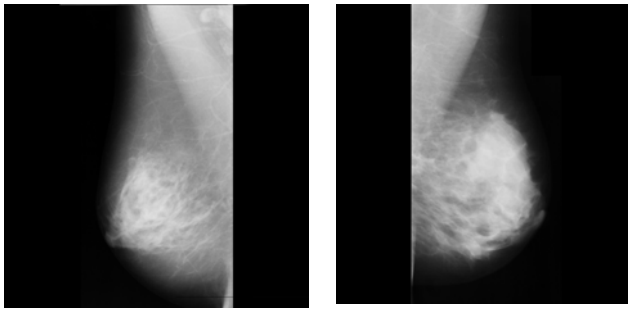

Fig 2. Mammographic images with microcalcifications

In order to decide on the appropriate wavelet for the mammographic image processing and enhancement, we have selected those images which included microcalcifications (24 images, in total) (Fig. 2).

D. Data processing

At the beginning of the process, we decomposed the mammographic images using different families of wavelets. The criterion of selecting the wavelet families was the orthogonality property of the wavelet. That is because it allows an input image to be decomposed into a set of independent coefficients, corresponding to each orthogonal basis. In other words, orthogonality implies that there is no redundancy in the information represented by the wavelet coefficients, which results in efficient representation and other desirable properties. Thus, we selected to run the experiments with Haar, Daubechies (DB), Coiflets (COIF) and Least Asymmetric Daubechies (SYM) wavelets.

The coefficients extracted by image decomposition were used to evaluate the percentages of energy corresponding to the horizontal, vertical and diagonal details.

III. Experimental Results

We experimented with the aforementioned types of wavelets aiming at incrementing the percentage of energy that corresponds to the horizontal, vertical and diagonal details of the third level of wavelet transform. At last the Least Asymmetric Daubechies' wavelets were proven to be the most promising wavelets. This choice is preferable since the Least Asymmetric Daubechies' wavelets have finite length and are nearly symmetric. Due to these features, they can achieve high correlation with the clustered microcalcifications, and, therefore, they can effectively enhance microcalcifications.

In Fig. 3, the experiment results are presented, in a comparative graph. In this graph, the percentages of energy

are grouped per wavelet and summed up in a single bar. The bigger the percentage of energy for an image is, the longer the respective bar is depicted. In this graph we have only considered the energy percentages corresponding to the details coefficients and not for the approximation; this was done due to the fact that, in fact, the approximation coefficients preserve almost 99 per cent of the total energy, which tallies to the background information.

It can be easily extrapolated from this figure that Least Asymmetric Daubechies 8 is the most appropriate to be chosen, when considering mammogram enhancement, since the respective energy is far higher, compared to the other wavelets.

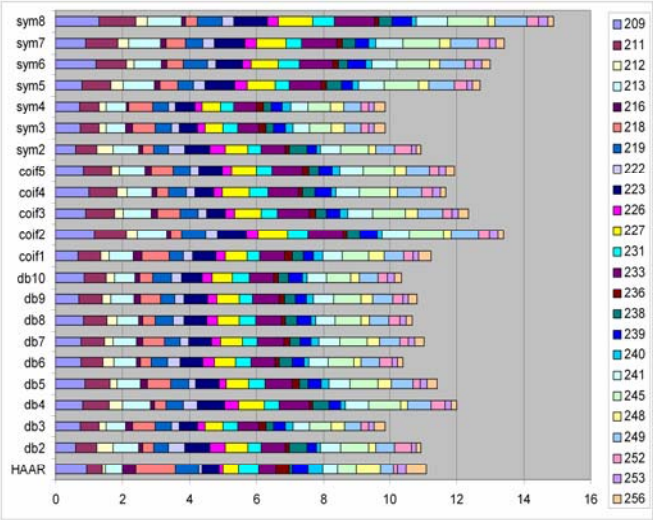

Fig 3. Results of the experiments of the application of different wavelet families on the mammographic images with microcalcifications. Y-axis indicates the various wavelets used for the experiments. The legend on the right corresponds to the ids of the MIAS mammograms, with which we experimented.

The experiments were accomplished by using the wavelet toolbox of Matlab 7.0 (Release14) [16].

IV. Conclusion

In this paper we presented a comparative study among the orthogonal wavelets, in order to decide on the appropriate family to be used for mammographic image processing. Image enhancement of mammographic images is a key solution in order to accomplish automatic detection of microcalcifications and favor early prognosis of breast cancer. The evaluation criterion for the decision of the wavelet was the degree of similarity between the wavelet and the image profile. This was assessed through the percentage of energy that corresponds to the coefficients of the wavelet transform. Our experimentation showed that the Least Asymmetric Daubechies wavelet with length 8 is the most appropriate, since it accumulates more energy corresponding to the details of the wavelet transform and moreover it is characterized by symmetry and finite length.

Among our next steps in our research, we can refer to the automatic determination of microcalcifications' clusters, the extraction of various characteristics based on texture, shape and intensity and, finally, the classification of microcalcifications according to these characteristics.

References

[1] World Health Organization, Cancer incidence, mortality and survival by site for 14 regions of the world. Available: http://www.who.int/healthinfo/paper13.pdf

[2] American Cancer Society, Breast Cancer Facts & Figures: Available: http://www.cancer.org/

[3] Regions: Statistical yearbook 2005 Data 1999-2003, Eurostat. Available: http://epp.eurostat.ec.europa.eu/cache/ITY_OFFPUB/KS-AF-05-001/EN/KS-AF-05-001-EN.PDF

[4] Sakka E., Prentza A. and Koutsouris D.: Classification algorithms for microcalcifications in mammograms (Review), Oncology Reports, SPECIAL ISSUE VOLUME 15, Computational analysis and decision support systems in oncology, 2006, pp 969-1108.

[5] Bazzani A, Bevilacqua A, Bollini D, Campanini R, Lanconelli N, Riccardi A and Romani D: Automatic detection of clustered microcalcifications using a combined method and an SVM classifier. ESANN'2000 proceedings - European Symposium on Artificial Neural Networks, Belgium, 2000, pp195-200

[6] Ferreira CBR and Borges DL: Analysis of mammogram classification using a wavelet transform decomposition. Pattern Recognition Letters 24, 2003, pp973–982

[7] Sentelle S, Sentelle C and Sutton MA: Multiresolution-Based Segmentation of Calcifications for the Early Detection of Breast Cancer. Real-Time Imaging 8, 2002, pp 237–252

[8] Soltanian-Zadeh H, Rafiee-Rad F and Pourabdollah-Nejad DS: Comparison of multiwavelet, wavelet, Haralick and shape features for microcalcification classification in mammograms. Pattern Recognition 37, 2004, pp1973–1986

[9] Lambrou T, Linney AD, Speller RD and Todd-Pokropek A: Statistical Classification of Digital Mammograms Using Features from the Spatial and Wavelet Domains. Medical Image Understanding and Analysis, Portsmouth, UK: 22-23, 2002

[10] Yoshida H, Doi K, Nishikawa RM, Muto K and Tsuda M: Application of the Wavelet Transform to Automated Detection of Clustered Microcalcifications in Digital Mammograms. Acad. Reports, Tokyo Inst. Polytech. 17: 24–37, 1994

[11] H. Yoshida, W. Zhangz, W. Cai, K. Doi, R. M. Nishikawa, and M. L. Giger: Optimizing wavelet transform based on supervised learning for detection of microcalcifications in digital mammograms, IEEE Proc. International Conference on Image Processing ICIP-95: 152-155, 1995.

[12] C. B. R. Ferreira, D. L. Borges: Analysis of mammogram classification using a wavelet transform decomposition, Pattern Recognition Letters 24, 2003, pp973–982

[13] Misiti, M., Misiti, Y., Oppenheim, G., Poggi, J.M.: Wavelet Toolbox User's Guide. MathWorks Inc., Massachusetts, (1996).

[14] I. Daubechies, Ten Lectures on Wavelets, CBMS-NSF Regional Conference Series in Applied Mathematics, No. 61, SIAM, Philadelphia, PA, 1992.

[15] The new MIAS Database. Available: http://www.wiau.man.ac.uk/services/MIAS/MIASfaq.html

[16] Matlab Wavelet Toolbox Available: http://www.mathworks.com/products/wavelet/