COMPUTER-AIDED DIAGNOSTIC SYSTEM BASED ON WAVELET ANALYSIS FOR MICROCALCIFICATION DETECTION IN DIGITAL MAMMOGRAMS

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Abstract- **Clusters of microcalcifications in mammograms are an important early sign of breast cancer in women. In this paper an approach is proposed to develop a Computer-Aided Diagnosis (CAD) system that can be very helpful for radiologist in diagnosing microcalcifications' patterns in digitized mammograms earlier and faster than typical screening programs. The proposed method has been implemented in three stages: (a) the region of interest (ROI) selection of 32×32 pixels size which identifies clusters of microcalcifications, (b) the feature extraction stage is based on the wavelet decomposition of locally processed image (region of interest) to compute the important features of each cluster and (c) the classification stage, which classify between normal and microcalcifications' patterns and then classify between benign and malignant microcalcifications. In classification stage, four methods were used, the voting K-Nearest Neighbor classifier (K-NN), Support Vector Machine (SVM) classifier, Neural Network (NN) classifier, and Fuzzy classifier. The proposed method was evaluated using the Mammographic Image Analysis Society (MIAS) mammographic databases. The proposed system was shown to have the large potential for microcalcifications detection in digital mammograms.**

Keywords - **Microcalcification, mammograms, wavelet, support vector machine, neural network, and fuzzy classifier.**

I. INTRODUCTION

Breast cancer is the most common cancer and continues to be a significant public health problem among women around the world. Primary prevention seems impossible since the cause of this disease still remains unknown [1]. It is believed that the most promising way to decrease the number of patient suffering from the disease is by early detection. The earlier breast cancer is detected, the better the chances that treatment will work and the better a proper treatment options can be provided.

To date, mammography remains the most effective diagnostic technique for early breast cancer detection; however, not all breast cancer can be detected by mammograms [2]. For microcalcifications (MCCs), the interpretations of their presence are very difficult because of its morphological features. For example, the sizes of MCCs are very tiny, typically in the range of 0.1mm- 1.0mm and the average is about 0.3mm, implying it can easily be overlooked by a radiologist. While in some dense tissues, and/ or skin thickening, MCCs areas are almost invisible to be seen by examining radiologist. The dense tissues especially in younger women may easily be misinterpreted as MCCs due to film emulsion error, digitization artifacts or anatomical structures such as fibrous strands, breast borders or hypertrophied lobules that almost similar to MCCs. Other factors that contribute to the difficulty of MCCs detection are due to their fuzzy nature, low contrast and low distinguish ability from their surroundings [1].

In the literature, various numbers of techniques are described to detect and classify the presence of microcalcifications in digital mammograms as benign or malignant. Yu and Guan [3] presented a CAD system for the automatic detection of clustered microcalcifications through two steps. The first one is to segment potential microcalcification pixels by using wavelet and gray level statistical features and to connect them into potential individual microcalcification objects. The second step is to check these potential objects by using 31 statistical features. Neural network classifiers were used. Mascio, Hernandez, and Clinton [4] developed a microcalcification detection algorithm, which operates on digital mammograms by combining morphological image processing with arithmetic processing. Netch [5] proposed a detection scheme for the automatic detection of clustered microcalcifications using multiscale analysis based on the Laplacian-of-Gaussian filter and a mathematical model describing a microcalcification as a bright spot of certain size and contrast. Barman, Granlund, and Haglund [6] used a low-pass filter to detect microcalcification by analyzing digital mammogram. Although the system based on their algorithm is still under development, good preliminary results have been produced with further modifications still to be made. Karssemeijer [7]–[9] developed a statistical method for detection of microcalcifications in digital mammograms. The method is based on the use of statistical models and the general framework of Bayesian image analysis. Chan *et al.* [10]–[12] investigated a computer-based method for the detection of microcalcification in digital mammograms. The method is based on a difference image technique in which a signal suppressed image is subtracted from a signal enhanced image to remove structured background in the mammogram. Zheng, Qian, and Clarke [13]–[15] proposed a method for the detection of microcalcifications clusters in digitized mammograms using mixed feature-based neural networks. Zaiane, Maria, and Alexandru [16] used neural network and data mining techniques for detection and classification of digital mammograms. Cheng, Lui, and Feiimanis [17] proposed an approach using fuzzy logic for the detection of microcalcifications. Pfrench, Zeidler, and Ku [18] presented a two–dimensional adaptive lattice algorithm to predict correlated clutters in the mammogram. Li, and Lo [19] proposed using fractal background modeling, taking the difference between the original and the modeled image, which results in enhanced MC detection.

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Strickland, and Hahn [20], [21] used a discrete wavelet transform (DWT) with biorthogonal spline filters to detect microcalcifications. Yoshida, Doi, and Nishikawa [22], [23] applied a DWT. They multiplied every scale by a weight factor and reconstructed an image by applying the inverse transform. The weights were determined by supervised learning, using a set of training cases. Clarke *et al.* [24] and Qian, Clarke, Kallergi, Zheng, and Clark [25], [26] applied a denoising to the image and then took the high-pass scale of a DWT using spline wavelets. This resulted in a general edge detector that could locate not only microcalcifications but also several other structures, such as film artifacts or lines. Bazzani *et al.* [27] proposed a method for MC detection based on multiresolution filtering analysis and statistical testing, in which an SVM classifier was used to reduce the false detection rate. Essam, Yongyi, and Mile [28] investigated an approach based on SVM for detection of microcalcification clusters in digital mammograms, and the sensitivity as high as 94% was achieved by the SVM. Wei, and Simoncelli [29] investigated several state-of-the-art machine-learning methods for automated classification of clustered microcalcifications in mammograms.

The remainder of the paper is organized as follows Section II gives a background of the wavelet analysis. Section III provides detailed information about the proposed system. Experiments performed and the results achieved are discussed in Section IV. Conclusions are drawn in Section V.

II. BACKGROUND

The proposed system is built based on wavelet analysis of the region of interest to extract features. Here we introduced the theoretical background for wavelet analysis.

A. Wavelet Analysis

Wavelet analysis is the most recent solution to overcome the shortcoming of the Fourier transform. Wavelet is a waveform of limited duration and can be expressed as mathematical functions that cut up data into different frequency components (into shifted and scaled versions of the original or mother wavelet) and then study each component with a resolution matched to its scale. The fundamental idea behind wavelet is to analyze according to scale. The spectrum is calculated each time it shifted and repeated many times with a slightly shorter or (longer) window every new cycle. So wavelet analysis allows the use of long time intervals where we want more precise low frequency and shorter regions where we want high-frequency information [30].

Wavelet analysis is based on three properties: orthogonality, quadratic filter and filter bank. Two functions *f* and *g* are said to be orthogonal to each other if their inner product is zero.

$$\langle f(t), g(t) \rangle = \int_a^b f(t) * g(t) dt = 0 \qquad (1)$$

The symbol * mean a convolution operation. Dilation and translation of the mother function or analyzing function achieved as shown in equation:

$$\varphi_{j,k}(x) = 2^{2/j} \varphi(2^j x - k) \qquad (2)$$

The variables *j* and *k* are integers that scale and dilate the mother function φ to generate wavelets. The scale index *j* indicates the wavelet's width and the location index *k* gives its location or (translation).

In the two dimensions wavelet analysis, two dimensions scaling functions $\varphi(i,j)$ and three 2D wavelets are required. These wavelet functions measure intensity or gray level variations for image along different directions.

$\Psi^H(x,y)$ responds to variation along columns (horizontal edge), $\Psi^V(x,y)$ responds to variation along rows (vertical edges) and $\Psi^D(x,y)$ measures variations along diagonals. The discrete wavelet transform of image $f(x, y)$ of size $M \times N$ is computed as follow: We first define the scaled and translated basis functions:

$$\varphi_{j,m,n}(x,y) = 2^{j/2} \varphi(2^j x - m, 2^j y - n) \qquad (3)$$

$$\psi_{j,m,n}(x,y) = 2^{j/2} \psi(2^j x - m, 2^j y - n) \qquad (4)$$

i: is a subscript that assumes values of H, V and D. then:

$$\psi_{\varphi}(j_0,m,n) = \frac{1}{\sqrt{MN}} \sum_{x=0}^{M-1} \sum_{x=0}^{N-1} f(x,y) \varphi_{0,m,n}(x,y) \qquad (5)$$

$$w_{\psi}^{i}(j_0,m,n) = \frac{1}{\sqrt{MN}} \sum_{x=0}^{M-1} \sum_{x=0}^{N-1} f(x,y) w_{\psi}^{i}(x,y) \qquad (6)$$

where

j_0: starting scale, we normally let it equal to zero.

$w_{\varphi}(j_0,m,n)$: define an approximation of $f(x,y)$ at the scale and normally obtained by convolving signal with the low -pass filter.

$w^i_{\psi}(j_0,m,n)$: define horizontal, vertical and diagonal details normally obtained using high - pass filter.

III. METHODOLOGY

The proposed system has three stages: preprocessing, feature extraction and classification process.

A. Preprocessing stage

In the preprocessing, the region of interest (ROI) was selected from the digital mammograms images.

A1. Mammogram image data source

It is difficult to access real medical images for experimentation due to privacy issue. The data collection that was used in our experiments was taken from the Mammographic Image Analysis Society (MIAS) [31]. It consists of 322 images, which belong to three categories: normal, benign and malign, which are considered abnormal. In addition, the abnormal cases are further divided into six categories: circumscribed masses, spiculated masses, microcalcifications, ill-defined masses, architectural distortion and asymmetry. All images are digitized at a

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resolution of 1024×1024 pixels and eight-bit accuracy (gray level). They also include the locations of any abnormalities that may be present. The existing data in the collection consists of the location of the abnormality (like the center of a circle surrounding the tumor), its radius, breast position (left or right), type of breast tissues (fatty, fatty-glandular and dense) and tumor type if exists (benign or malign).

A2. ROI Selection

Using the locations of any abnormalities supplied by the MIAS for each mammogram, the ROI of size 32×32 pixels is extracted with microcalcification centered in the window, and divided into two sets: the training set and the testing set. We used 100 images for normal cases, and 25 images for microcalcification cases (13 benign images and 12 malignant images).

B. Features Extraction

Features are extracted from the ROI based on the wavelet decomposition process. These features are passed to the classification stage. There are five processing steps in the features extraction stage [2]. Features, in our system, are extracted from the coefficients that were produced by the wavelet analysis decomposition. In this section we discuss these steps.

B1. Wavelet Decomposition

In this work, the wavelet decomposition applied on the region of interest using matlab toolbox**.** The output of wavelet analysis are the decomposition vector C and corresponding book keeping matrix S, The vector C consist from horizontal, vertical, and diagonal detail coefficients and one approximation.

B2. Coefficients Extraction

The horizontal, vertical and diagonal detail was extracted from the wavelet decomposition structure [C, S]. These vectors were extracted at each scale from scale 1 to 3.

B3. Normalization

The coefficients vectors for scales 1 to 3 are normalized after extracted. The normalization process is achieved by dividing each vector by its maximum value. The results of this operation is that all vectors values become less than or equal one. The normalization process is used to simplify the coefficients value.

B4. Energy Computation

We compute the energy for each vector by squaring every element in the vector. The produced values are considered as features for the classification process.

B5. Features Reduction

From the wavelet decomposition, it produces high number of coefficients. Therefore, at the last phase, we reduce the number of features by estimated the mean for each wavelet coefficient at each scale.

C. Classification

The classification process is divided into the training phase and the testing phase. In the training phase, labeled data are given. Separately, the data on a candidate region which has already been decided as a microcalcification or as normal are given, and the classifier is trained. In the testing phase, unknown data are given and the classification is performed using the classifier after training. The number of images which were used in training and testing sets are shown in Table 1.

We used four techniques, the voting K-Nearest Neighbor (K-NN) classifier, Support Vector Machine (SVM) classifier, Neural Network (NN) classifier, and Fuzzy classifier to classify between normal and microcalcification tissues, and to classify between benign and malignant microcalcification tissues.

C1. Voting K-Nearest Neighbor (K-NN) classifier

The Voting k-Nearest Neighbor (k-NN) classifier is nonparametric technique, it assigns a test sample to the class of the majority of its K-neighbors; that is, assuming that the number of voting neighbors is $k=k_1+k_2+k_3$ (where k_i is the number of samples from class i in the k-sample neighborhood of the test sample), the test sample is assigned to class m if $k_m = \max \{k_i, i=1, 2, 3\}$ [32]. Through this study, we compared the results of using k=1 to k=11.

C2. Support Vector Machine (SVM) classifier

SVM has the potential to handle very large feature spaces, because the training of SVM is carried out so that the dimension of classified vectors does not has as distinct an influence on the performance of SVM as it has on the performance of conventional classifier. That is why it is noticed to be especially efficient in large classification problem. This will also benefit in faults classification, because the number of features to be the basis of fault diagnosis may not have to be limited. Also, SVM-based classifier is claimed to have good generalization properties compared to conventional classifiers, because in training SVM classifier the so-called structural misclassification risk is to be minimized, whereas traditional classifiers are usually trained so that the empirical risk is minimized. The performance of SVM in various classification task is reviewed, e.g., in Christiani and Shawe-Taylor [33]. Through this study, we used linear kernel function.

C3. Neural Network (NN) classifier

A back propagation neural network (BPNN) was used for classification of features into normal or microcalcification, and then into benign or malignant microcalcification.

C4. Fuzzy classifier

The fuzzy classifier based on the Fuzzy C-Mean (FCM) clustering which provided by matlab toolbox in order to classify between normal and microcalcification patterns, and then classify between benign and malignant microcalcification.

TABLE 1
Number of training and testing sets

Category	No. of image	No. of training set	No. of testing sets
Normal	100	75	25
Microcalcification	25	18	7
Benign	13	9	4
Malignant	12	8	4

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IV. RESULTS & DISCUSSIONS

Results from the proposed system obtain in two steps; first we obtained results of classification between normal and microcalcification images from four classifiers shown in table 2, 3, 4, and 5. Second we obtained results of classification between benign and malignant microcalcifications images from four classifiers shown in table 6, 7, 8, and 9.

Table 2 shows results of classification rates for normal and microcalcifications (MCCs) by using K-NN classifier for testing set with varying the k value (1-11) and at different levels of wavelet decomposition (levels 1-3, levels 1-2, and levels 2-3).

In table 3, 4, and 5 show results of classification rates for normal and microcalcifications (MCCs) by using SVM, fuzzy, and BPNN classifiers for testing set at different levels of wavelet analysis (levels 1-3, levels 1-2, and levels 2-3).

These results demonstrate that four classifiers with different levels of wavelet decomposition give the best results. But the classification rate of microcalcification cases achieves the best performance with features extracted from levels 1–3, and levels 2-3 because microcalcification is small and represented as high frequency information details which embodied in the highest levels by wavelet decomposition. On the other hand, the classification rate of microcalcification cases achieves the bad performance with features extracted from levels 1–2 because the low frequency information which embodied in the lowest levels by wavelet decomposition.

Table 6 shows results of classification rates for benign and malignant microcalcification by using K-NN classifier for testing set with varying the k value (1-11) and at different levels of wavelet decomposition (levels 1-3, levels 1-2, and levels 2-3).

In table 7, 8, and 9 show results of classification rates for benign and malignant microcalcification by using SVM, fuzzy, and BPNN classifiers for testing set at different levels of wavelet analysis (levels 1-3, levels 1-2, and levels 2-3).

From the above results the best results of classification rates for benign and malignant microcalcification obtained by K-NN classifier at k = 11, and levels 1-3, SVM classifier at levels 1-3, fuzzy classifier at levels 1-3, and BPNN classifier at levels 2-3. We noted the best results achieved at level 1-3, and level 2-3, because benign and malignant are small and represented as high frequency information details which embodied in the highest levels by wavelet decomposition.

These results are not so much satisfactory because small number cases for benign and malignant were used in training and testing the system which does not cover the entire space of each cluster.

TABLE 2
Classification rates for normal and MCCs by using K-NN classifier

k	Levels 1-3		Levels 1-2		Levels 2-3	
	Normal (%)	MCCs (%)	Normal (%)	MCCs (%)	Normal (%)	MCCs (%)
1	100	100	100	25	100	100
3	100	100	100	12.5	100	100
5	100	100	100	12.5	100	100
7	100	100	100	0	100	100
9	100	100	100	0	100	100
11	100	100	100	0	100	100

TABLE 3
Classification rates for normal and MCCs by using SVM classifier

Levels 1-3		Levels 1-2		Levels 2-3	
Normal (%)	MCCs (%)	Normal (%)	MCCs (%)	Normal (%)	MCCs (%)
100	100	96	12.5	100	100

TABLE 4
Classification rates for normal and MCCs by using Fuzzy classifier

Levels 1-3		Levels 1-2		Levels 2-3	
Normal (%)	MCCs (%)	Normal (%)	MCCs (%)	Normal (%)	MCCs (%)
75	100	100	12.5	100	100

TABLE 5
Classification rates for normal and MCCs by using BPNN classifier

Levels 1-3		Levels 1-2		Levels 2-3	
Normal (%)	MCCs (%)	Normal (%)	MCCs (%)	Normal (%)	MCCs (%)
100	100	72	37.5	100	100

TABLE 6
Classification rates for benign and malignant by using K-NN classifier

k	Levels 1-3		Levels 1-2		Levels 2-3	
	Benign (%)	Malignant (%)	Benign (%)	Malignant (%)	Benign (%)	Malignant (%)
1	50	75	25	75	75	50
3	25	100	50	50	75	50
5	50	100	50	50	50	75
7	75	75	25	75	75	50
9	75	25	25	75	75	50
11	100	100	25	100	100	50

TABLE 7
Classification rates for benign and malignant by using SVM classifier

Levels 1-3		Levels 1-2		Levels 2-3	
Benign (%)	Malignant (%)	Benign (%)	Malignant (%)	Benign (%)	Malignant (%)
75	100	50	50	75	75

TABLE 8
Classification rates for benign and malignant by using Fuzzy classifier

Levels 1-3		Levels 1-2		Levels 2-3	
Benign (%)	Malignant (%)	Benign (%)	Malignant (%)	Benign (%)	Malignant (%)
75	100	25	100	100	50

TABLE 9
Classification rates for benign and malignant by using BPNN classifier

Levels 1-3		Levels 1-2		Levels 2-3	
Benign (%)	Malignant (%)	Benign (%)	Malignant (%)	Benign (%)	Malignant (%)
25	75	50	50	75	75

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V. CONCLUSION

In this study, a computer-aided diagnostic system using wavelet analysis for microcalcification detection in the digitized mammograms of the breast is presented. This system depends on selecting some features from different levels of wavelet decomposition and using them in the classification process. Experiments were conducted on the MIAS dataset to diagnose microcalcification in a fully automatic manner using wavelet analysis and four classifiers.

The results suggest that proposed system can aid in the microcalcification detection in digital mammograms. It is hoped that more interesting results will follow on further exploration of data. Although developed method is built as an offline diagnosing system, it can be rebuilt as an online diagnosing system in the future.

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