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Detection and Classification of Microcalcifications Using Discrete Wavelet Transform

Anuradha C. Phadke[1], Preeti P. Rege[2]

[1,2] Department of Electronics & Telecomm. Engg., College of Engineering, Pune, 411005 INDIA

Abstract: ***Microcalcifications in mammograms are an important early sign of breast cancer and their early detection is very important to improve its diagnosis. Many times microcalcification clusters are missed by radiologists due to its small size. Computer-based detection system can assist the radiologist to improve the diagnostic accuracy. This paper presents an approach for detection and classification of microcalcifications in digital mammograms. Given that the microcalcifications correspond to high-frequency components of the image spectrum, detection of microcalcifications is achieved by decomposing the mammograms into different frequency subbands using wavelet transform, scaling the high frequency sub-band and finally, reconstructing the mammogram using scaled high frequency sub-band. Classification of microcalcifications into benign and malignant classes is done using wavelet features and two types of classifiers, Support Vector Machine and Artificial Neural Network Classifier. Classification accuracy achieved with Artificial Neural Network Classifier is 96.15% which is greater than that with Support Vector Machine Classifier.***

Keywords: Artificial Neural Network (ANN), Computer-Aided Detection (CAD), Mammograms, Microcalcifications, Support Vector Machines (SVMs).

1. INTRODUCTION

Women suffering from Breast cancer have been taken as a serious concern all around the world, as it directly affects the next generation to come. A very important component of cancer prevention and treatment is detection. The earlier a tumor is detected the easier is the treatment. This is especially the case for malignant tumors. Early discovery can catch the carcinoma while they are still in their In Situ stage, where they have not spread through the body. Currently, MAMMOGRAPHY is the most effective imaging modality in early breast cancer detection, particularly in finding non- palpable small lesions (less than 1 cm in diameter). Early detection reduces breast cancer mortality by about 25%. However, interpretation of mammograms is not easy.

The radiologists experience plays a meaningful role in the process of diagnosis. The most common signs of breast cancer are masses and calcifications. Masses are big and clearly present in the mammogram. Unlike calcifications, which are very small and therefore hard to detect and see. The presence of calcifications may be easily missed or misinterpreted by radiologists while reading large amounts of mammograms provided in screening programs.

A wavelet based image enhancement technique using Artificial Neural Network is implemented by J.S.Leena Jasmine, Dr.A.Govardhan, Dr.S.Baskaran [5]. In [10] Ferreira C.B.R.; Borges D.L. propose to construct and evaluate a supervised classifier for classification of microcalcifications, by transforming the data of the images in a wavelet basis, and then using special sets of the coefficients as the features.

The methods used by José Salvado, Bruno Roque [7] involve image de-noising, wavelet image analysis and image enhancement by local adaptive operators integrated in the wavelet domain. The image is decomposed in sub-bands, the low-frequency sub-band is suppressed and then the image is reconstructed from the high-frequency sub-bands by Ted C. Wang and Nicolaos. B. Karayiannis [11]. T.Balakumaran, Dr.ILA.Vennila, C.Gowri Shankar [3] have proposed an algorithm for mammogram quality enhancement using multirresolution analysis based on the dyadic wavelet transform and microcalcification detection by fuzzy shell clustering.

Carmen Serrano, Javier Díaz-Trujillo, Begoña Acha and Rangaraj M. Rangayyan [8] proposed method based on region growing with pre-filtering and a seed selection procedure based on two-dimensional linear prediction error. Anna N. Karahaliou, Ioannis S. Boniatis, Spyros G. Skiadopoulos, Filippos N. Sakellaropoulos, Eleni Likaki, George S. Panayiotakis and Lena I. Costaridou [9] proposed texture based method for detection of microcalcifications. Texture features are extracted from the remaining ROI area (surrounding tissue) employing first and second order statistics algorithms, grey level run length matrices and Laws' texture energy measures. Differentiation between malignant and benign MCs is performed using a k-nearest neighbour (kNN) classifier and employing the leave-one-out training-testing methodology. V. Alarcon-Aquino, O. Starostenko, J. M. Ramirez-Cortes, R. Rosas-Romero, J. Rodriguez-Asomoza, O. J. Paz-Luna and K. Vazquez-Muñoz [6] 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. In [4] Albert Torrent *et al.* use a supervised approach for automatic detection of micro-calcifications. The system is based on learning the different morphology of the micro-calcifications using local features, which are extracted using a bank of filters.

Rest of the paper is organized as follows: Section 2 explains structure of the proposed system for microcalcification detection and classification. Section 3 explains theoretical background of wavelet transform and how it is used for microcalcification detection. Section 4 describes the system implementation. In section 5 experimental results are presented and section 6 gives concluding remarks.

2. METHODOLOGY

The objective of this work is to develop a system which can detect and classify microcalcifications in mammograms. Figure 1 shows the system block diagram.

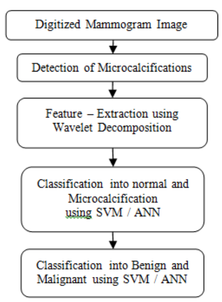

Figure 1 System Block Diagram

2.1 Microcalcification Enhancement

Microcalcifications appear in digital mammograms as groups of small localized granular bright spots due to their higher X-ray attenuation compared to the normal breast tissue. Visibility of microcalcifications is often degraded by the high frequency texture of the breast tissue. For increasing the visibility of the microcalfications which makes the detection easier, the detection step can be preceded by enhancement of the mammogram.

2.2 Microcalcification Detection

Given that the microcalcifications correspond to high frequency components of the image spectrum and wavelets can localize the signal characteristics in both frequency and scale, our hypothesis is that the resolution and scale of the microcalcifications in the spatial domain can be preserved if we use wavelet filters to decompose the mammogram into different frequency subbands. According to this hypothesis, microcalcifications can be extracted from mammograms by suppressing the sub band of the wavelet-decomposed image that carries the lowest frequencies and enhancing the sub band of the wavelet-decomposed image that carries the high frequencies. The reconstruction of weighted higher frequency subbands provides better visibility of microcalcifications than the other breast regions. Since microcalcification appears as high frequency behavior in mammogram, the enhancement is achieved by enhancing detail coefficients as per the equation number (1).

$$F_i^{D}(x,y) = \begin{cases} S_i^{D}(x,y) & \text{if } |S_i^{D}(x,y)| < T_i \\ a * S_i^{D}(x,y) & \text{if } |S_i^{D}(x,y)| >= T_i \end{cases} \qquad (1)$$

where, x and y are spatial coordinates, D represents all horizontal, vertical and diagonal subbands. T_i be a non negative threshold obtained by taking standard deviation of respective subimage. The visibility of microcalcifications is obtained by multiplying high frequency subbands by the gain ‘a’. The reconstruction of weighted higher frequency subbands provides better visibility of microcalcification region than the other breast regions.

2.3 Feature Extraction

The cropped image of size 256x256 was decoposed into 7 levels by applying Daubechies4 wavelet transform. It results in four subbands namely low frequency subband, horizontal, vertical and diagonal subbands. Wavelet coefficients from these Horizontal, Vertical and Diagonal subbands are used as features for classification of mammograms. Total 147 wavelet coefficients of the image are used as the feature vector.

2.4 Classification

There are two stages of classification. First the mammograms are classified into normal and microcalcification tissues using wavelet features. In the second stage, individual microcalcification objects are classified as benign or malignant using set of features extracted using wavelet transform. In this work, two types of classifiers are used namely Artificial Neural Network (ANN) and Support Vector Machine (SVM).

2.4.1 Support Vector Machine (SVM)

The SVM uses an optimum linear separating hyperplane to separate two set of data in a feature space. This optimum hyperplane is produced by maximizing minimum margin between the two sets. Therefore the resulting hyperplane will only be depended on border training patterns called support vectors [1], [14]. SVM schemes use a mapping into a larger space so that cross products may be computed easily in terms of the variables in the original space making the computational load reasonable. The cross products in the larger space are defined in terms of a kernel function $K(x, y)$ which can be selected to suit the problem.

2.4.2 Artificial Neural Network (ANN)

In this paper a Backpropagation algorithm is used for learning in the neural network. Learning is a process by which neural network adapts itself to stimulus and eventually it produces a desired response. The desired output from the network is whether the mammogram is normal or microcalcification. During the training session of the network a pair of data is presented, the input data (wavelet coefficients) and the target or the desired data (normal or microcalcification). At the output layer, the difference between the actual and target outputs yields an error signal. This error signal depends on the values of the weights of the neurons in each layer. This error is minimized, and during this process new values for the weights are obtained [2].

3. WAVELET ANALYSIS

Wavelet analysis is appropriate for detection and classification of microcalcifications as it decomposes the image into well localized, interpretable components that make local features in the image easily accessible. It decomposes an image into coefficients that describe the local geometry of the image in terms of scale and orientation [12], [13]. It has the additional advantage of being flexible with respect to image resolution and robust with respect to varying image quality. The strong mathematical basis and the different properties of the wavelet transform have been utilized for the purpose of enhancement, detection and classification of microcalcifications. Figure 2 shows subbands at different resolutions produced by two levels of wavelet decomposition.

The wavelet transform uses basis functions that can dilate in scale and translate in position according to the signal characteristics. Given that the microcalcifications correspond to high frequency components of the image spectrum and wavelets can localize the signal characteristics in frequency and scale, our hypothesis is that the resolution and scale of the microcalcifications in the spatial domain can be preserved if we use wavelet filters to decompose the mammogram into different frequency subbands. According to this hypothesis,
microcalcifications can be extracted from mammograms by suppressing the subband of the wavelet-decomposed image that carries the lowest frequencies and contains smooth (background) information, before the reconstruction of the image.

Wavelet-based image decomposition can be interpreted as an image filtering process. For a given image A of size 2^n x 2^n , wavelet-based subband decomposition can be performed as follows:

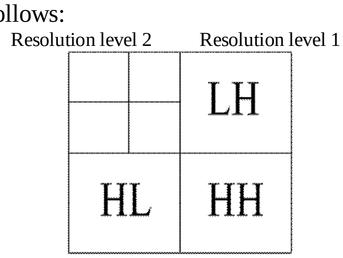

Figure 2 Orthogonal subbands produced by two levels of wavelet decomposition

The wavelet filters $h_1(n)$ and $h_2(n)$ are applied to the rows of the image A. The filter $h_1(n)$ is a low-pass filter with frequency response $H_1(w)$ and $h_2(n)$ is a highpass filter with frequency response $H_2(w)$. By filtering the image A with $H_1(w)$, we obtain low-frequency information (background). By filtering the image with $H_2(w)$, we obtain the high-frequency information (edges). After down-sampling by a factor of two, we obtain two subbands H_{1rA} and H_{2rA} (the subscript suggests that the filters are applied to rows of the image A). Since we down-sample by a factor of two in the horizontal direction of each subband, the size of these two down-sampled subbands is 2^n x 2^n-1. The filters $H_1(w)$ and $H_2(w)$, are then applied to the columns of the subbands H_{1rA} and H_{2rA}, followed by down-sampling by a factor of two, and the following four subbands are obtained: $H_{1c}H_{1rA}$ (LL), $H_{2c}H_{1rA}$ (LH), $H_{1c}H_{2rA}$ (HL) and $H_{2c}H_{2rA}$ (HH). Since we now down-sample by a factor of two in the vertical direction of each subband, the four subbands have gone through down sampling by a factor of two in both directions and the final size of each subband is 2^n-1 x 2^n-1. This process of wavelet decomposition of the image is shown in Figure 3. The subband $H_{1c}H_{1rA}$ contains the smooth information and the background intensity of the image and the subbands $H_{2c}H_{1rA}$, $H_{1c}H_{2rA}$ and $H_{2c}H_{2rA}$ contain the detail information of the image. The subband $H_{1c}H_{1rA}$ corresponds to the lowest frequencies, $H_{2c}H_{1rA}$ gives the horizontal high frequencies

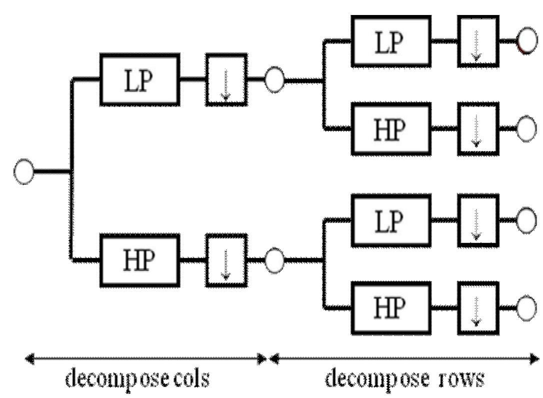

Figure 3 Wavelet Decomposition of Image

(vertical edges), $H_{1c}H_{2rA}$ gives the vertical high frequencies (horizontal edges), and $H_{2c}H_{2rA}$ gives the high frequencies in both directions (corners and diagonal edges).

Using the mentioned process cropped image is decoposed into 7 levels by applying Daubechies4 wavelet transform. It results in four subbands namely low frequency subband, horizontal, vertical and diagonal subbands. Wavelet coefficients from these Horizontal, Vertical and Diagonal subbands are used as features for classification of mammograms. Total 147 wavelet coefficients of the image are used as the feature vector.

4. SYSTEM IMPLEMENTATION

4.1 Database Resource

A mammogram is a low dose x-ray of the breast. The mammogram images used in this experiment are taken from the mini mammography database of MIAS (Mammogram Image Analysis Society). The database contains 322 mammogram images in MLO (mideolateral oblique view). The original MIAS Database images are clipped/padded so that every image is 1024 pixels × 1024 pixels. In this work, the images were cropped to size 256x256 pixels. The MIAS database was provided with the diagnosis from experts.

A set of 52 images is used wherein 26 images are normal, 26 images are microcacified. Out of 26 abnormal images 15 are having benign microcalcifications and 11 are having malignant microcalcifications. These 26 images are divided into training and testing set.

4.2 Detection of Microcalcifications

Following steps are used to detect microcalcifications and to form feature vector which is used to classify the mammograms.

- Read the image and convert it to gray scale.
- Perform thresholding to remove the irrelevant pixel intensities.
- Decompose the image using Daubechies-4 (db4) filter. Perform decomposition for 7 levels.
- The image we get contains two parts:
  - Approximation Coefficients
  - Detail coefficients (horizontal, vertical and diagonal details)
- Use 147 wavelet coefficients as feature vector for the classification of mammograms.
- Now scale the Detail (Horizontal, Vertical and Diagonal) coefficients by a gain of 1.2.
- Perform inverse Wavelet Decomposition using the approximation co-efficient we got after decomposition and the detail coefficients we got after scaling. We use the same Daubechies filter (db4) for inverse transformation.
- We can now observe the microcalcifications if present. They separate out as the small spots of calcium deposits having bright intensity pixels.
- We perform adaptive thresholding on this resultant image using a 3x3 mask to get a clearer view of the calcifications.
- If microcalcifications are not detected the image is classified as normal image.

4.3 Classification of Microcalcifications

The feature vectors of the training set are used to train the SVM and ANN classifier and for discriminating Normal, benign and malignant microcalcifications. Then a test set is given to the classifiers to classify each of the images in it.

5. RESULTS

In this work a system to detect and classify mammograms is implemented. Figure 4 shows results of microcalcification detection using wavelet transform based method.

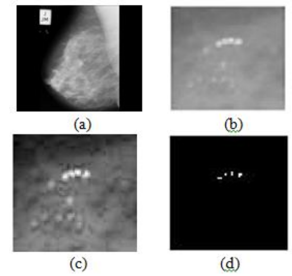

Figure 4 (a) Original Mammogram (b) Cropped image (c) Enhanced image using wavelet transform (d) Detected Microcalcifications

Tabel 1: Results of classification into normal & microcalcifications

Classifier	Sensitivity (%)	Specificity (%)	Accuracy (%)
SVM	75.60	81.25	79.58
ANN	98.08	100.00	99.04

Tabel 2: Results of classification into benign & malignant microcalcifications

Classifier	Sensitivity (%)	Specificity (%)	Accuracy (%)
SVM	65.16	76.67	69.30
ANN	95.45	96.66	96.15

There are two stages of classification. First the mammograms are classified into normal and microcalcification tissues using wavelet features. Results of this classification using SVM and ANN classifiers are shown in Table 1. It is seen that accuracy of classification of normal & microcalcification using SVM is 80% and that using ANN is 99%.

In the second stage, individual microcalcification objects are classified as benign or malignant using wavelet features. Results of this classification using SVM and ANN classifiers are shown in Table 2. It is seen that the accuracy of classification of benign and malignant microcalcification using SVM is 69% and that using ANN is 96%.

6. CONCLUSION

From the results we can conclude that, combination of wavelet features and ANN classifier gives best accuracy of classification of mammograms. By comparing results for ANN and SVM classifier for both the Tabels, Tabel 1 and Tabel 2 we can conclude that ANN classifier gives better sensitivity, specificity and accuracy of classification than SVM classifier for mammogram classification of normal and microcalcified mammograms. Even for classification of benign and malignant microcalcifications ANN classifier gives better performance than performance of SVM classifier.

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AUTHOR

Anuradha C. Phadke received BE and ME degree from Walchand College of Engineering, Sangli, India in 1993 and 1995 respectively. Since 1995 she has been with Maharashtra Institute of Technology, Pune, India where she is currently working as Associate Professor at Department of Electronics and Telecommunication Engineering. She has published and presented many papers in national and international conferences, journals and published two books. She is pursuing Ph.D. at University of Pune in "Mammogram Image Analysis" under the guidance of Dr. Priti P. Rege

Priti P. Rege received the B.E. and M.E. (Gold medal) degrees from Devi Ahilay University of Indore, India, and the Ph.D. degree from the University of Pune, India, in 2002. Since 1989, she has been with the College of Engineering Pune, where she is currently working as a Professor and Dean Academics in the Department of Electronics and Telecommunications. Her research interests include signal processing and pattern recognition. Several of her papers have appeared in leading journals and conferences. Dr. Rege was the recipient of "Nagarkar Fellowship" for carrying out research in subband coding of images.