Detection of Microcalcification Clusters in Mammograms using Neural Network

Dheeba.J
Research Scholar, Computer Science and Engineering
Anna University
Tirunelveli , TN, India
deeps_3u4@yahoo.com

Wiselin Jiji.G
Prof & Head, Computer Science and Engineering
Dr. Sivanthi Adithanar College of Engineering
Tiruchendur, TN, India
jijivevin@yahoo.com

Abstract

This paper presents a new classification approach for detection of microcalcification clusters in digital mammograms. The proposed microcalcification detection method is done in two stages. In the first stage, features are extracted to discriminate between textures representing clusters of microcalcifications and texture representing normal tissue. The original mammogram image is decomposed using wavelet decomposition and gabor features are extracted from the original image Region of Interest (ROI). With these features individual microcalcification clusters is detected. In the second stage, the ability of these features in detecting microcalcification is done using Backpropagation Neural Network (BPNN). The proposed classification approach is applied to a database of 322 dense mammographic images, originating from the MIAS database. Results shows that the proposed BPNN approach gives a satisfactory detection performance.

Keywords**: **Computer Aided Diagnosis, Microcalcification, Mammograms, Backpropagation Neural Network, Gabor features, Integer wavelet transform (IWT).

1. Introduction

Breast cancer is one of the frequent and leading cause of mortality among woman, especial in developed countries. Age is one of the risk factor of breast cancer. Women within the age of 40-69 have more risk of breast cancer. In western countries about 53%-92% of the population has this disease. In a Phillipine study [1] a mammogram screening was done to 151,198 women. Out of that 3479 women had this disease and was referred for diagnosis. Though breast cancer leads to death, early detection of breast cancer can increase the survival rate. The current diagnostic method for early detection of breast cancer is mammography. Mammographies are low dose X-ray projections of the breast, and it is the best method for detecting cancer at the early stage.

Microcalcifications (MC) are quiet tiny bits of calcium, and may show up in clusters or in patterns and are associated with extra cell activity in breast tissue. Usually the extra cell growth is not cancerous, but sometimes tight clusters of microcalcification can indicate early breast cancer. Scattered microcalcifications are usually a sign of benign breast cancer. 80% of the MC is benign. MC in the breast shows up as white speckles on breast X-rays. The calcifications are small; usually varying from 100 micrometer to 300 micrometer, but in reality may be as large as 2mm. Though it is very difficult to detect the calcifications as such, when more than 10 calcifications are clustered together, it becomes possible to diagnose malignant disease. But the survival depends on how early the cancer is detected. So, any MC formation should be detected at the benign stage. Hence, a Computer Aided Diagnosis (CAD) system is used to detect MC clusters.

Many different algorithms have been proposed for automatic detection of breast cancer in mammograms. Features extracted from mammograms can be used for detection of cancers [2]. Studies reports that features are extracted from the individual MCs [3] or from the ROI which contain MC clusters [4].

Joaquim.C. Felipe *et al*. [5] uses a set of shape based features. The paper presents the task of calcification and similarity retrieval of mammographic masses based on shape content. It also uses the statistical based association rule to discriminate the disease from the normal breast tissue. In [6] Chen *et al*. presents a new texture shape feature coding (TSFS) based classification method for classifying masses on mammograms. A texture shape histogram is used for generating various shape features of masses. Khuzi.A.M *et al.* [7] used a gray level co-occurrence matrix to provide the texture content information of Region of interest at different angles. Pelin Gorgel *et al.* [8] designed a wavelet based Support Vector Machine (SVM) for capturing information of the MCs. Decision making is done by extracting features as a first stage by computing wavelet coefficients and classification using the classifier trained on the extracted features. Prabhu shetty.K *et al.* [9] uses the spatial decomposition property of the Discrete Wavelet Transform and based on the statistical analysis the MC clusters are classified. Sonayang u *at al.* [10] used a wavelet features and gray level statistics features based general regression neural networks. Lei Zheng *et al.* [11] presents an algorithm that combines several artificial intelligent techniques with the discrete wavelet transform for detection of masses in mammograms.

These computerized methods discussed in the previous paragraphs did not analyze the texture component of the image in detail. Gabor features [25] are used in several image analysis applications including texture classification and proved to be efficient.

The major objective of this paper is to take multiple texture features from the original image to discriminate between microcalcification and the normal tissue in the breast. As a first stage, the original image is decomposed using Integer Wavelet Transform (IWT) and features are extracted from the decomposed image using gabor features. In the second stage, the extracted features are compared by means of their ability in detecting microcalcification clusters using BackPropagation Neural Network (BPNN). We use mammograms from the Mammographic Image Analysis Society (MIAS) database which contain 322 mammograms [12].

2. Materials

2.1 A Database of Mammograms and preprocessing

The UK research group has generated a MIAS database of digital mammograms. The database contains left and right breast images of 161 patients. Its quantity consists of 322 images, which belongs to three types such as Normal, benign and malignant. The database has been reduced to 200 micron pixel edge, so that all images are 1024 x 1024. There are 208 normal, 63 benign and 51 malignant (abnormal) images. It also includes radiologists 'truth' marking on the locations of any abnormalities that may be present. The database is concluding of four different kinds of abnormalities namely: architectural distortions, stellate lesions, Circumscribed masses and calcifications.

As a preprocessing step, the breast area is separated from the background image. This saves the processing rime and also the memory space. For the purpose of training the BPNN, the images are randomly selected from the database. 115 images are used for training the network and 207 images are used for testing.

3. Methodology for detecting microcalcification

We propose a novel approach to computer-aided diagnosis of breast cancer using mammographic findings. This is illustrated using the flowchart shown in Figure.1.

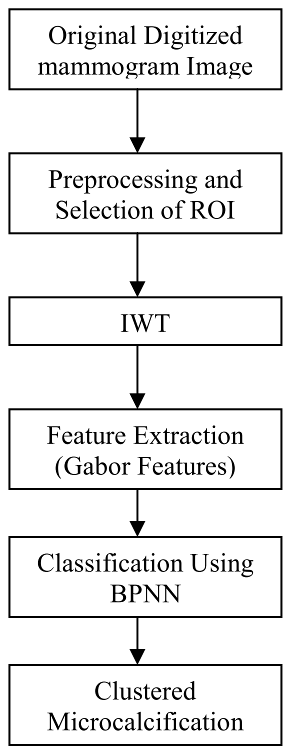

Figure. 1 Flowchart of our proposed CAD System

3.1 Integer Wavelet Transform

The wavelet transform is widely acknowledged to feature excellent decorrelation properties [16], [17] and it exhibits excellent lossy compression performance, and has been selected for the new standard JPEG 2000 [13]. In fact, followed by efficient encoders which exploit the intra and interband residual correlation [18], and suitable rate-distortion optimization techniques [14], [15], the DWT allows to form finely scalable bitstreams [13], [19]. A more efficient approach to lossless compression is the use of integer transforms, such as the integer wavelet transform (IWT) [20]–[22]. The transform coefficients exhibit the feature of being exactly represented by finite precision numbers, and this allows for truly lossless encoding.

The lossless and lossy image compression performance of the IWT have already been reported in the literature [22], [23]; Recently, the lifting scheme (LS) [24] has been introduced for efficient computation of the DWT. Its main advantage with respect to the classical filter bank structure lies in its better computational efficiency and in the fact that it enables a new method for filter design. Moreover, the IWT can be computed starting from any real valued wavelet filter by means of a straightforward modification of the LS [22]. Therefore, the LS represent a distinguished choice for the implementation of encoders with progressive lossy-to-lossless compression capabilities, providing a common core for computing both the DWT and the IWT.

3.2 Gabor Features Extraction

The word texture is in general regarded as surface appearance or tactile qualities. A texture can be regarded as a self-similar object. In image processing the texture of a region describes the pattern of spatial variation of gray tones (or in the different color bands in a color image) in a neighborhood that is small compared to the region. By definition, texture classification is to identify the texture class in a region, whereas texture segmentation means finding a boundary map between different textures regions of an image [24]. There is an ambiguity here since classification can be used for segmentation. We use the term texture classification in the following even though the goal of the classification is segmentation. Most texture classification algorithms start by finding a local feature vector which in turn is used for classification. Texture classification using learned (over complete) dictionaries and sparse representation is a relatively new area in texture classification.

The Gabor wavelet was first introduced by David Gabor in 1946. The use of features based on Gabor filters has been promoted for their useful properties in image processing. The most important properties are related to invariance, illumination, rotation, scale, and translation. These properties are based on the fact that they are all parameters of Gabor filters themselves. This is especially useful in feature extraction, where Gabor filters have succeeded in diverse applications, like texture analysis.

The Gabor wavelet is a sinusoidal plane wave with a particular frequency and orientation, modulated by a Gaussian envelope. It can characterize the spatial frequency structure in the image while preserving information of spatial relations and, thus, is suitable for extracting the orientation-dependent frequency contents of patterns.

Also, the use of Gabor filters in extracting textured image features is motivated by various factors. The Gabor representation has been shown to be optimal in the sense of minimizing the joint two-dimensional uncertainty in space and frequency. These filters can be considered as orientation and scale tunable edge and line (bar) detectors, and the statistics of these micro features in a given region are often used to characterize the underlying texture information.

A two dimensional Gabor function $g(x, y)$ and its Fourier transform

$G(u, v)$ can be written as:

$$g(x,y) = \left(\frac{1}{2\pi\sigma_x\sigma_y}\right)\exp\left[-\frac{1}{2}\left(\frac{x'^2}{\sigma_x^2}+\frac{y'^2}{\sigma_y^2}\right)+2\pi jW_x\right]$$

$$G(u,v) = \exp\left\{-\frac{1}{2}\left[\frac{(u-W)}{\sigma_u^2}+\frac{v^2}{\sigma_v^2}\right]\right\}$$

where $\sigma_u = 1/2\pi\sigma_x$ and $\sigma_v = 1/2\pi\sigma_y$ gabor functions form a complete but nonorthogonal basis set. Expanding a signal using this basis provides a localized frequency description. A class of self-similar functions, referred to as Gabor wavelets in the following discussion, is now considered. Let g(x, y) be the mother Gabor wavelet, then this self-similar filter dictionary can be obtained by appropriate dilations and rotations of *g(x, y)* through the generating function:

$$g_{mn}(x,y) = a^{-m}G(x',y'), a>1,\ m, n = \text{integer}$$

$$x' = a^{-m}(x\cos\theta + y\sin\theta),\ \text{and}\ y' = a^{-m}(-x\sin\theta + y\cos\theta),$$

Where, $\theta = n\pi/K$ and K is the total number of orientations. The scale factor a^{-m} is meant to ensure that the energy is independent of m.

The nonorthogonality of the gabor filters implies that there is redundant information in the filtered images, and the following strategy is used to reduce this redundancy. Let U_l and U_h denote the lower and upper center frequencies of interest. Let K be the number of orientations and S be the number of scaled in the multiresolution decomposition. The filter parameters σ_u and σ_v (and thus σ_x and σ_y) are computed using the following formulas.

$$a = (U_h/U_l)^{-\frac{1}{S-1}}$$

$$\sigma_u = \frac{(a-1)U_h}{(a+1)\sqrt{2\ln 2}}$$

$$\sigma_v = \tan\left(\frac{\pi}{2k}\right)\left[U_h - 2\ln\left(\frac{\sigma_u^2}{U_h}\right)\right]\left[2\ln 2 - \frac{(2\ln 2)^2\sigma_u^2}{U_h^2}\right]^{-\frac{1}{2}}$$

Where *W=* U_h and *m=0,1,...., S-1.* In order to eliminate sensitivity of the filter response to absolute intensity values, the real components of the gabor filters are biased by adding a constant to make then zero mean.

3.3 Neural Network classification

In order to find the potential microcalcification pixels based on the above mentioned features, a proper classification method must be used. In our study, the classifier chosen is a multilayer feedforward neural network [26]. The main reason for choosing it is because of its nonparametric statistical property. Unlike the classical statistical classification methods, such as the Bayes classifier, no knowledge of the underlying probability distribution is needed by a neural network. It can learn the free parameters (weights and biases) through training by using examples. This makes it suitable to deal with real problems which are nonlinear, nonstationary, and nonGaussian. The neural network classifier is used to generate a likelihood map of each mammogram using the gabor features as the input to the classifier. The pixel value in the likelihood map shows the possibility of that pixel being classified as a microcalcification pixel. The larger the value, the more likely it is a microcalcification pixel. The multilayer feedforward neural network used is a three layer network with one hidden layer of six units. There are four units in the input layer corresponding to the mixed feature vector of each pixel and two units in the output layer corresponding to microcalcification pixels and normal pixels, respectively. The output unit corresponding to the true microcalcification pixels is then thresholded to segment out the true microcalcification pixels. The training data set for the above neural network is chosen from the 115 ROI's with a cluster of microcalcifications in the center. If one microcalcification pixel is picked out from one ROI, a corresponding normal pixel is chosen randomly from the same ROI. This makes the number of microcalcification pixels equal to the number of normal pixels in the training data set. After training, the neural network is used to classify the 207 full mammograms in the database.

3.4 Proposed Backpropagation Learning

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. Learning is also a continuous classification process of input stimuli. During the process of learning the network adjusts its parameters, the synaptic weights in response to and input stimulus so that its actual output response converges to the derived output response.

2160 gabor features are given as input to the network for training. The desired output from the network is whether the calcification is malignant, benign, or normal tissue. 120 neurons are used in the hidden layer. During the training session of the network a pair of patterns is presented, the input pattern (gabor features) and the target or the desired pattern (malignant, benign, or normal). 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. The proposed backpropagation network is shown in Figure 2.

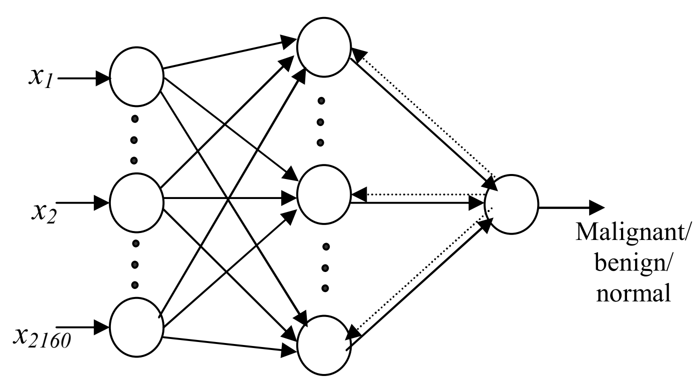

Figure. 2. Proposed Backpropagation Network

The error back – propagation algorithm can be outlined as

1. Initialize all weights to small random values.
2. Choose an input-output training pair.
3. Calculate the actual output from each neuron in a layer by propagating the signal forward through the network layer by layer (forward propagation).
4. Compute the error value and error signals for output layer. The error signals is given by

$$E(w) = \frac{1}{2} * \sum (d_i - y_i)^2$$

   and d_i and y_i are the desired output and the actual output respectively.
5. Propagate the errors back ward to update the weights and compute the error signals for the preceding layers.
6. Check whether the whole set of training data has been cycled once, yes – go to step 7; otherwise go to step 2.
7. Check whether the current total error is acceptable; yes- terminate the training process and output the field weights, otherwise initiate a new training epoch by going to step 2.

4. Classification of soft tissue lesions/masses in mammograms and performance evaluation

All experiments in this chapter are performed on digitized mammograms from the MIAS database provided by the Mammographic Image Analysis Society (MIAS) in the UK [23]. The images from this database have a resolution of 50 microns (0.05 mm/pixel), 8 bits pr. pixel.

The proposed method segments/classifies the input mammogram into suspicious and non-suspicious regions (i.e. normal breast tissue and malignant tissues). Our aim was that no case of malignancy-indicating microcalcification should escape radiological analysis. We therefore started from two basic assumptions: (i) the microcalcifications have an aspect that differentiates them from the other elements of the breast because of their different X-ray opacity; and (ii) since we are looking for microcalcifications that are in an incipient stage, they involve a very small proportion of the total area of the breast because they otherwise would be clearly visible to any radiologist and there would consequently be no point in using our system.

(a) (b)

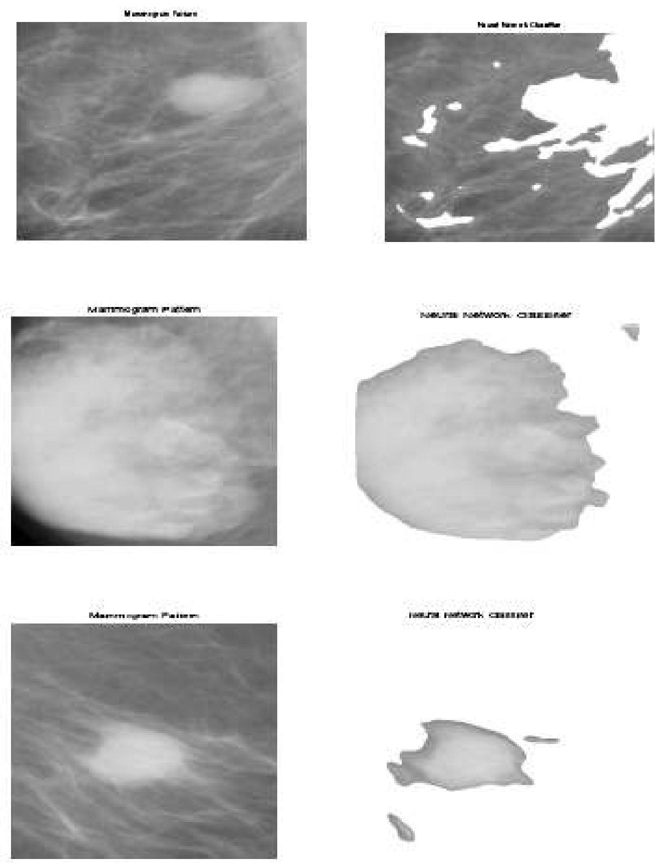

Figure 3. (a) Mammogram image
(b) Neural Network classified tumor patterns

The detection results for various mammogram patterns are illustrated in Figure. 3. Since those regions in a mammogram corresponding to tumor tissues have different texture patterns and gray levels than the normal ones, it is possible to classify these regions.

5. Conclusion

We present a novel approach to the problem of computer-aided analysis of digital mammograms for breast cancer detection. The algorithm developed here classifies mammograms into normal & abnormal. First, the structures in mammograms produced by normal glandular tissue of varying density are eliminated using a Integer Wavelet Transform (IWT) based local average subtraction. The gabor features are extracted and classification approaches using artificial neural networks shows good classification results. Using the mammographic data from the Mammographic Image Analysis Society (MIAS) database a recognition score of 84.3% was achieved using the proposed approach.

6. References

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Authors

Dheeba.J, received the B.E degree in Computer Science and Engineering from Anna University, Chennai in the year 2005 and M.E degree in Computer Science and Engineering from Anna University, Chennai in the year 2007. She is currently working towards the Ph.D degree in the department of Information and Communication Engineering, Anna University, Tirunelveli. Her research interest includes Medical Image Processing, Soft Computing and Artificial Intelligence.

Dr.G.Wiselin Jiji, received the B.E degree in Computer Science and Engineering from Manonmanium Sundarnar University, Tirunelveli in the year 1994 and M.E degree in Computer Science and Engineering from Madurai Kamaaraj University, Madurai in the year 1998. She received her Ph.D in Information and Communication Engineering from Anna University, Chennai in the year 2008. Currently she is the Professor and Head of Computer Science and Engineering in Dr.Sivanthi Aditanar college of Engg, Tiruchenthur. She is a reviewer in Computer Vision and Image Understanding (Elsevier) and AMSE International Journal. Her research interest includes Medical Image Processing: Feature Extraction, Clustering, Texture Analysis, Pattern Recognition, and Image Compression.