A Neural Network Method for Mammogram Analysis Based on Statistical Features

M.G. Mini and Tessamma Thomas
Department of Electronics
Cochin University of Science & Technology
Cochin, Kerala, India
phone: 91-484-2576418; fax: 91-484-2575800;
mimini@ieee.org, tessamma@ece.ac.in

Abstract— In this paper, 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 and abnormal. First, the structures in mammograms produced by normal glandular tissue of varying density are eliminated using a Wavelet Transform (WT) based local average subtraction. Then the linear markings formed by the normal connective tissue are identified and removed. Any abnormality that may exist in the mammogram is therefore enhanced in the residual image, which makes the decision regarding the normality of the mammogram much easier. Statistical descriptors based on high-order statistics derived from the residual image are applied to a Probabilistic Neural Network (PNN) for classification. Using the mammographic data from the Mammographic Image Analysis Society (MIAS) database a recognition score of 71% was achieved.

1. INTRODUCTION

Breast cancer is a leading cause of fatality in women. X-ray mammography is currently the most popular, cost-effective, low radiation dose and relatively accurate method of early detection of the disease. The radiographs are searched for signs of abnormality by expert radiologists but mammograms are complex in appearance and signs of early disease are often small or subtle. That is the main reason of many missed diagnoses that can be mainly attributed to human factors [1,2]. Since the consequences of errors are costly, there has been a considerable interest in developing methods for automatically classifying mammographic abnormalities, as a means of aiding radiologists by improving the efficacy of screening programs and avoiding unnecessary biopsies.

Most of the Computer Aided Diagnosis (CAD) schemes for breast cancer detection aims at detecting one or more of the three abnormal structures in mammograms [3]: microcalcifications [4], circumscribed masses [5], spiculated lesions [6], which often characterize early breast cancer [7]. Masses appear as dense regions of varying sizes and properties and can be characterized as circumscribed, spiculated and ill defined. On the other hand, microcalcifications appear as small bright arbitrarily shaped regions on the large variety of breast texture background. Finally, asymmetry and architectural distortions are also very important and difficult to detect. The great variability of the mass appearance along with the other abnormalities in digital mammograms is the main obstacle of building a unified mass detection method.

Heine, et al [8] used a statistical method based on wavelet expansion to separate normal regions from potentially abnormal regions containing isolated calcifications. Neural network CAD schemes for detecting masses in mammograms, such as microcalcifications, have already been used [9-13]. Many have explored classifying breast lesions as benign or malignant [14]. However, little work has been done on recognizing normal mammograms. Prescreening mammograms to identify the relatively large number of clearly normal mammograms, as well as large areas of clearly normal tissue in potentially abnormal mammograms will substantially reduce the workload of radiologists, which in turn, would increase the accuracy of their diagnosis in subtle cases.

Our approach to the normal mammogram recognition problem is based on normal tissue identification and removal, which is independent of the types of abnormalities that may exist in the mammogram. The classification is achieved by presenting the higher order statistical
Fig1: Normal Mammograms having different types of tissue.
(a) dense-glandular type (b) fatty type (c) fatty-glandular type

descriptors derived from the residual image to a neural network classifier.

2. NORMAL MAMMOGRAMS

Completely normal mammograms may have entirely different appearances and there is no clear definition of normal mammograms [15]. Figure 1 shows examples of different, entirely normal mammograms. As there is no spikes corresponding to microcalcifications and no large bright areas corresponding to masses they have a lower overall density than abnormal ones. Normal regions have linear markings, which are shadows of ducts and connective tissue elements. These are distinct from spiculated or stellate lesions, in which linear markings radiate locally in all directions [6]. Normal linear markings in mammograms can be considered as straight-line segments of dimensions 1 to 2 mm or greater in length and 0.1 to 1mm in width. Removal of the normal background and linear markings enhances the contrast and obviousness of abnormal structures making their detection easier. In addition, the normal tissue recognition problem is fundamentally simpler and easier for computers to solve than is the tumor detection problem, because the properties of images of normal tissue are much simpler than the properties of images of abnormalities of various types, sizes, and stages of development.

3. NEURAL NETWORK CLASSIFIERS

Neural networks have been widely used in situations where the expert knowledge is not explicitly defined and cannot be described in terms of statistically independent rules. We have selected PNN for classification purpose, which has 2 layers. When an input is presented, the first layer computes distances from the input vector to the training input vectors, and produces a vector whose elements indicate how close the input is to a training input. The second layer sums these contributions for each class of inputs to produce as its net output a vector of probabilities. Finally, a complete transfer function on the output of the second layer picks the maximum of these probabilities, and produces a one for that class and a 0 for the other classes. The architecture for this system is shown below in fig 2.

The implemented feature extraction procedure relies on the texture, which is the main descriptor for all kinds of mammograms. In this paper, we concentrate on statistical descriptors that include averages, standard deviations, and higher-order statistics of intensity values. Four gray level sensitive histogram moments, mean ($\mu$), variance ($\sigma^2$), skewness ($\mu_3$) and kurtosis ($\mu_4$) are extracted from the pixel value histogram of the residual image as defined below:

\[
\mu = \frac{\sum_{k=1}^{N} f_k n_k}{n} \quad (1)
\]
\[
\sigma^2 = \frac{\sum_{k=1}^{N} (f_k - \mu)^2 n_k}{n} \quad (2)
\]
\[
\mu_3 = \frac{1}{\sigma^2} \sum_{k=1}^{N} (f_k - \mu)^3 n_k / n \quad (3)
\]
\[
\mu_4 = \frac{1}{4} \sum_{k=1}^{N} (f_k - \mu)^4 n_k / n - 3 \quad (4)
\]

where $N$ denotes the number of gray levels in the mammogram, $f_k$ is the $k^{th}$ gray level, $n_k$ is the number of pixels with gray-level $f_k$ and $n$ is the total number of pixels in the region considered.
4. PROPOSED METHOD

The proposed method consists of 4 steps: the removal of normal background, detection and removal of linear markings, feature extraction and PNN based classification. The normal background region is removed using a WT based average subtraction technique. Edges are identified by extracting the local edge points and then grouping them into lines. This method has a disadvantage that it does not respond well to thick lines because pixels in the middle of a thick line are not edge pixels. The selected features, mean, variance, skewness and kurtosis are extracted from the residual image and presented to a PNN, which groups the image into one of the two classes: normal and abnormal.

5. RESULT AND DISCUSSION

The algorithm has been validated using mammograms from the freely available database provided by the MIAS [16]. The images in the database are digitized at 50-micron pixel edge, which are then reduced to 200-micron pixel edge and clipped or padded so that every image is having 1024 x 1024 pixels. The accompanied ‘Ground Truth’ contains details regarding the character of the background tissue, class and severity of the abnormality and x, y coordinate of its centre and radii. 259 Regions of Interest (ROI) of size 256 x 256 were selected from the MIAS database for validation of the proposed method. The selected ROIs included 153 normal ones and 106 ROIs containing various kinds of abnormal tissues like microcalcifications, circumscribed masses, spiculated lesions and combinations of these abnormalities. 102 (52 abnormal ones and the rest normal) ROIs from these were used to train the PNN. 100% detection accuracy was obtained for the training set.

The network is tested using the 157 ROIs (Excluding the training set). The recognition accuracy is 70.8%, considering the normal ROIs alone and 72% for the abnormal ones alone. The results are expressed in terms of three parameters, True Positive (TP), False Positive (FP) and False Negative (FN). A TP is obtained when a normal/abnormal mammogram is correctly classified into normal/abnormal class. When a normal mammogram is incorrectly classified as abnormal, it is defined as a FP. A FN is obtained when an abnormal mammogram is incorrectly classified into normal class. The results are tabulated in Table 1.

<table>
<thead>
<tr>
<th>Table 1: Recognition score</th>
</tr>
</thead>
<tbody>
<tr>
<td>No. of ROIs</td>
</tr>
<tr>
<td>Normal</td>
</tr>
<tr>
<td>Abnormal</td>
</tr>
<tr>
<td>Total</td>
</tr>
</tbody>
</table>

The accuracy of the detection algorithm depends on the efficiency of the linear marking removal algorithms. The common line detection algorithms are not suitable for detecting lines of varying width. The popular line detection method, Hough transform cannot be applied here, as it is not suitable for grey-level images. For getting high detection accuracy, a better line detection algorithm is to be developed.
REFERENCES


