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Detection of micro-calcifications in mammogram images using probabilistic neural network

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ABSTRACT

This paper presents a novel method for early detection of forming a Tumor i.e. Micro-calcifications in Mammograms. The main objective of this paper is to segment and detect the Micro-calcification (MCCs) from Digital mammograms that helps to provide and support for clinical decision to perform biopsy of the breast. In this paper, there are two aspects. First is to enhance the image by using Mathematical Morphology and denoise by Wavelet Transform and segmentation and detection of Micro-calcifications using Spot detection. Second is to extract texture based features by using Gabor filters from the segmented image and finally classify it by using Probabilistic Neural Network (PNN) classifier. The Mammogram database consist of 154 images, in which 90 images are taken for training the Probabilistic neural network and 64 images are used for testing purpose.

Introduction

Introduction

Breast cancer is a leading cause of fatality among all cancers for women. However, the etiologists of breast cancer are unknown and no single dominant cause has emerged. Still, there is no known way of preventing breast cancer but early detection allows treatment before it is spread to other parts of the body.

Currently, X-ray Mammography associated with clinical breast examination is the only viable and effective method at present for mass screening to detect breast cancer.

Early stage for the sign of breast cancer disease is about 30-50% of Mammographically detected cases, it includes appearance of clusters of fine, granular Micro-calcifications which are tiny granule like deposits of calcium of size 0.3mm to 0.7mm. However, the sensitivity of mammography is highly challenged by the presence of dense breast Parenchyma and fatty glandular tissue, which deteriorates both detection and Characterization tasks.

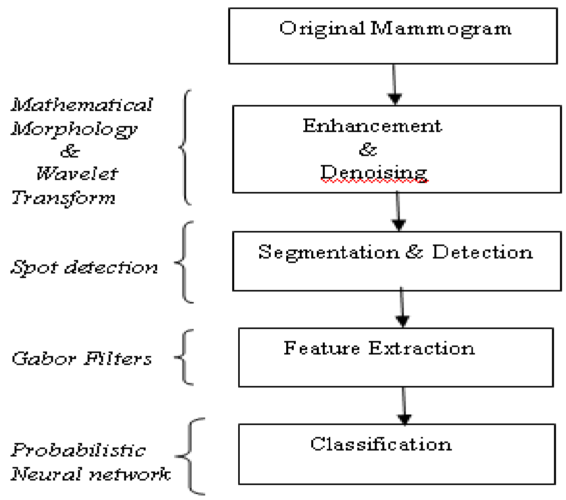
In the literature survey, number of techniques has described to enhance and detect the presence of MCCs in digital mammograms. The Methods which are less computation intensive than existing approaches are proposed in this paper for detection of Micro calcifications [1, 2, 3].

The above block diagram describes as follows; Original digital mammogram image is taken as input, and then it is enhanced by using Mathematical Morphology and denoised by Wavelet Transform. After that, the denoise image is given for segmentation and detection of Micro-calcifications using Spot detection method, then it is further processed for Feature extraction using Gabor filter and finally it is classified by using Probabilistic Neural Network (PNN) classifier.

The rest of the paper is organized as follows. Section II, describes the enhancement and denoising algorithms, Section III discusses Segmentation & detection, Section IV gives of feature Extraction, Section V Classify the mammogram images based on Normal and abnormal conditions, Section VI shows the Quantitative measurements & experimental results.

Methodology

The block diagram for detection of Micro-calcification as shown in Figure 1



Enhancement

To increase the contrast enhancement of image, here two methods are used. First is based on Mathematical morphology and the second one is based on wavelet analysis.

Mathematical Morphology:

A top-hat is a residual filter which preserves those features in an image that can fit inside the structure element and removes those that cannot. We used the structuring element *A* as a disc of radius 15. The top-hat by opening, *ho* (1) is defined as the difference between the original image, *f*, and its gray scale opening, *f o*, using the structure element A.

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$$ho = f - (f o A) \quad (1)$$
$$hc = (f . A) - f \quad (2)$$
$$M = f + ho - hc \quad (3)$$

Similarly, the top-hat by closing, *hc* is defined in (2). The dual residual *M* is obtained, as given in (3).

This reduces high frequencies in image (i.e. noise) However, a drawback of the mathematical morphology technique is that a part of the noise still remains. To remove the remaining noise, we use the Wavelet transform. [2]

Wavelet Transform:

Here bioorthogonal (Daubechies wavelets) have been used. Denoising means Image recovery from noisy data an can be expressed as

$$S(x, y) = f(x, y) + \sigma\, e(x, y) \quad (4)$$

The main objective of denoising is to suppress the noise part of the image *S* and to recover the original image f, which is added to the noise level e and supposed to be equal to1 and σ is Gaussian white noise with unit variance.

Generally denoising procedure involves three stages:

Wavelet decomposition:

Compute the wavelet decomposition of the image S at level N.

Threshold detail coefficients:

Select and apply a threshold to the detail coefficients for each level from 1 to *N*, here soft-thresholding has been used. It has been shown that thresholding by using bio-orthogonal transform outperforms.

The soft threshold signal is as follows:

$$f(x) = \begin{cases} \operatorname{sign}(x)(|x|-t) & \text{if } |x|>t \\ 0 & \text{if } |x|\leq t \end{cases} \quad (5)$$

$$t = \frac{m_1 + (\alpha * n_2)}{n_3 * n_1}, \quad m_1 > 0 \quad (6)$$

We use a threshold which is computed by using local statistics of the original mammogram as given in. (6)

Where 0□□α□□1, n_1 the mean intensity value, n_2 is the standard deviation, n_3 is the median value and m_1 is minimum value of the original mammogram. [2, 3]

Reconstruction process:

Perform a wavelet reconstruction using the last approximation coefficients and the modified details coefficients of levels from N to 1.

By combining the mathematical morphology scheme with the wavelet scheme we can get good results [3]. The steps of the proposed Enhancement (i.e. denoising) algorithm are given below.

Step1: Take Original mammogram image as input.

Step 2: Use morphological Top-Hat algorithm

Step3: Decompose the mammogram using Daubechies wavelets.

Step4: Apply soft thresholding method to find details coefficients at a threshold value.

Step5: Reconstruct the image using Daubechies wavelets.

Segmentation & Detection

After pre-processing phase, which in turn leads to ease segmentation for extracting the regions of interest (ROI) from the background, by using Spot detection method.

Spot detection and Segmentation

The proposed approach uses a two-stage algorithm for spot detection and shape extraction.

The Spot Detection Process:

The first step is to make the detection process independent of background gray level. This is implemented by filtering stage to separate the background signal from lesions. This is achieved by using high-pass filter H(x, y).

$$H(x, y) = B(x, y) - BL(x, y) \quad (7)$$

Where B(x y) is original image and BL(x, y) is the Low pass filtered values of the original image using Gaussian filter G(x, y) of width 'σ'.

$$BL(x, y) = G\sigma(x, y) * B(x, y) \quad (8)$$

Gaussian smoothing Kernel is given by

$$G\sigma(x, y) = \frac{1}{2\pi.\sigma^2} \exp[-(x^2 + y^2)/2.\sigma^2] \quad (9)$$

The filtered image H(x, y) has the negative value relative to the background. The 'σ' has to be chosen larger than the maximum expected size of the spots, In order to remove negative part, since it does not contain any information about micro-calcification ,so we are taking $\sigma = 4$.

$$P(x, y) = \max(0, H(x, y)) \quad (10)$$

Here P(x, y) has only positive values which are less than or equal to maximum gray level.

To make independent of noise level, two Gaussian kernels of different weights are taken and convolved with P(x, y).

$$I(x, y) = (w . G\sigma^{+}(x, y) - G\sigma^{-}(x, y)) * P(x, y) \quad (11)$$

Here $o+$ and σ^{-} are positive and negative kernel of width and Weight w is always chosen less than 1.

I(x, y) is a non-negative signal.

$$I(x, y) > T \quad (12)$$

Threshold value 'T' is selected in two steps. First, standard deviation of the image I(x,y) is calculated and first threshold, K times this standard deviation is applied. In the next step again the standard deviation is calculated in the parts above the threshold.

The final threshold is set K times to recalculate the standard deviation.

The Gaussian filtering smoothens the boundaries of the spots and also the shape of the spots is distorted to preserve the shape, here we have to reconstruct the shape of the spot back. For detail explanation of Weighted Difference of Gaussian operation is explained in [4, 5]

Reconstructing the Shape of the Spots:

Morphological filter operation is used to preserve the shape of the spot. First the image is enhanced by operating operation.

$$S(x, y) = M\ DILA(M\ ERO\ B(x, y)) \quad (13)$$

Where, M is the structuring element. To recover the positive peaks; opened image is subtracted from the original image

$$R(x, y) = B(x, y) - S(x, y) \quad (14)$$

R(x, y) is thresholded, so that some parts of noise are removed. The shapes of the spots are reconstructed back by applying a morphological conditional thickening operation as given below.

Reconstruction by Conditional Thickening operation:

The purposes, of doing morphological conditional thickening is to extend the shape of the spot to detect MCCs by Gaussian filter until the boundaries of spots are detected.

(M1, M2)CTHICKENING I. R=

$$R \cap (I \cup ((M1\ ERO\ I) \cap (M2\ ERO\ I^{C}))) \quad (15)$$

Where I^{C} is the compliment of the image I(x, y) and I represent the result of detection process by Gaussian filter and R is result of reconstruction giving the shape of the spots by morphological filter.

Feature Extraction

Gabor filters:

In this work, Texture based features are extracted from the segmented image by using Gabor filters. [7]

A texture can be regarded as a self-similar object. Most texture classification algorithms start by finding a local feature vector which, in turn is used for classification. This is especially useful in feature extraction, where Gabor filters have succeeded in diverse applications.

A two dimensional Gabor function g(x, y) and its Fourier transform G (u, v) can be written as:

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

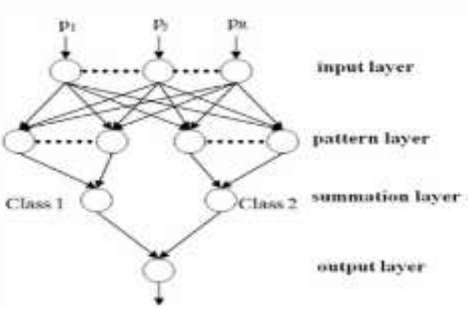
$$G(u,v) = \exp\left\{-\frac{1}{2}\left[\frac{(u-W)}{\sigma^2}+\frac{v^2}{\sigma^2}\right]\right\} \quad (16)$$

Where $\sigma = 1/2\sigma x$ and $\sigma = 1/2\sigma y$ gabor functions form a complete but nonorthogonal basis set. σ_x and σ are the filter parameters. [7, 8]

Classification

Probabilistic Neural Network:

Probabilistic Neural Network (PNN) is a class of radial basis function (RBF) network, which is useful for automatic pattern recognition nonlinear mapping and estimation of probabilities of class membership and likelihood ratios. The PNN consists of nodes with four layers namely input, pattern, summation and output layers as shown in Figure 2.



Benign/ Malignant

Figure 2 PNN Architecture

The input layer consists of merely distribution units that give similar values to the entire pattern layer. For this work, RBF is used as the activation function in the pattern layer. The function is sent to the radial basis transfer function. The ||dist|| box (17) subtracts the input weights, from the input vector P, and sums the squares of the differences to find the Euclidean distance. The differences indicate how close the input is to the vectors of the training set. These elements are multiplied element by element, with the bias b function and sent to the radial basis transfer function.

The output a is given as:

$$a = radbas\,(||IW - P||\, b) \quad (17)$$

Where *radbas* is the radial basis activation function.

The summation layer shown in Figure 2 simply sums the inputs from the pattern layer which correspond to the category from which the training patterns are selected as either class 1 or class 2 finally; the output layer of the PNN is a binary neuron that produces the classification decision. As for this work, the classification is either class 1 for Benign cases or class 2 for Malignant cases.

Training &Testing:

The network was trained with all 90cases (50 benign and 40 malignant cases). When the training process is completed for the training data (90 cases), the last weights of the network were saved to be ready for the testing procedure. The output of the network was 1 for the class benign and 2 for the class malignant. The time needed to train the training datasets was approximately 0.87 second. The testing process is done for 64 cases (35 benign and 29 malignant). These 64 cases are fed to the proposed network and their output is recorded for calculation of the sensitivity, specificity and accuracy. [9, 10, 11]

Quantitative measurements and experimental results

The classification has been done by using Probabilistic Neural Network (PNN) classifier.

Table 1 shows the results of Benign and Malignant images using PNN classifier.

The performance of the PNN algorithm has evaluated by computing the percentages of Sensitivity *(SE)*, Specificity *(SP)* and Accuracy *(AC)*, the respective definitions are as follows:

$$SE = \frac{TP}{(TP+FN)} * 100 \quad (18)$$

$$SP = \frac{TN}{(TN+FP)} * 100 \quad (19)$$

$$AC = \frac{TP+TN}{(TN+TP+FN+FP)} * 100 \quad (20)$$

Where,

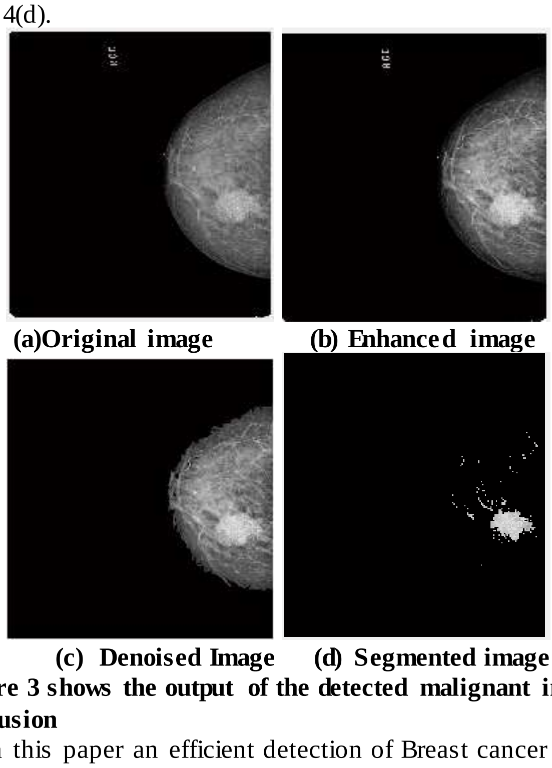
TP: True Positive, Malignant regions with correct detection.
FP: False Positive, Regions with incorrect malignant detection.
TN: True Negative, Benign regions with correct detection.
FN: False Negative, Regions with incorrect benign detection.

Table 2, 3 shows the performance of probabilistic Neural Network classifier for *AC, SE and SP* by using test data.

Figures 3 and figure 4 shows, the outputs of Malignant and Benign images.

Here in figure 3(a) shows the original Malignant image as input and it is enhanced, which is shown in figure 3(b), the denoised image is shown in figure 3(c) and segmented image is shown in figure 3(d).

The figure 4 (a) shows the original Benign image as input and it is enhanced, which is shown in figure 4(b), the denoised image is shown in figure 4(c) and segmented image shown in figure 4(d).



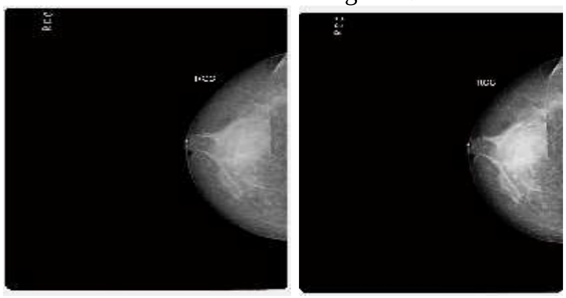
(a)Original image **(b) Enhanced image**

(c) Denoised Image **(d) Segmented image**

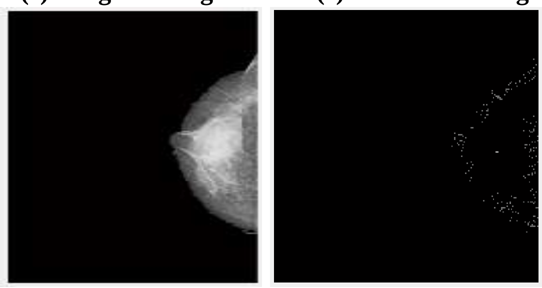
Figure 3 shows the output of the detected malignant image.

Conclusion

In this paper an efficient detection of Breast cancer Micro-calcifications algorithms for digital mammograms has been introduced. It is based on Mathematical Morphology and a Wavelet-based-level dependent thresholding algorithm has been applied to increase contrast in mammograms.



(a) Original image **(b) Enhanced image**



(c) Denoised image **(d) Segmented image**

Figure 4 shows the output of the detected benign image.

The paper clearly explains the methodology of Mammogram segmentation and classification, in which how Spot detection is applied to segment and detect the micro-calcification (MCCs) and to extract the features from segmented MCC using Texture features using Gabor filter and classify the micro-calcifications from mammograms by using Probabilistic Neural Network (PNN) classifier method, which shows a good classification rate. The classification rate is in between 88% to 90%.

Accuracy is calculated to evaluate its effectiveness of the proposed PNN network. The obtained accuracy of the network was 89.06% whereas the Sensitivity and Specificity were found to be equal 86.66% and 91.11% respectively.

We conclude that the proposed system gives fast and accurate classification of Malignant and Benign Mammograms. The Mammogram data base collected from Piramal Diagnostics (KCDC) Mysore.

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Table 1 Probabilistic neural network results of benign, malignant image

Database	Benign	Malignant
Number of training images	50	40
Number of tested images	35	29
Correct classification	31	26
Rate of classification	88%	89%

Table 2 Classifications of breast microcalcification by PNN classifier

Data classes	Classification with PNN	
Benign	FN=4	TN=31
Malignant	TP=26	FP=3
Total	35	29

Table 3 Performance of PPN to classification

PNN performance features	Performance of network
Accuracy	89.06%
Sensitivity	86.66%
Specificity	91.11%