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Detection of lesions in medical image using an artificial neural networks and morphological filters

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Abstract

Artificial neural networks are used many areas in digital image processing. The present method contains a back propagation algorithm is efficiently used to classify the detected lesion in medical image analysis. The method is performed by consider the digital mammograms. The proposed method consists sub parts of pre processing, feature extraction, and classifications. Pre processing has designed by using mathematical morphology filters, feature extraction has concentrated on two region of interests one is distributed micro classifications and cluster detection. In order improve the accuracy micro calcifications is used an edge based detection algorithm, for cluster detection a morphological curvelet transform is applied. Lesions are classified used a benign and malignant. This method performance given a FROC for evaluations. These results are compared with present existed method. The method is implemented in MATLAB13 .Simulation of the algorithm has shown an improved results.

Keywords*: Computer aided detection, mammography, morphological Filters, edge detection, curvelet Back propagation network, FROC*

1. Introduction

Cancer is one of the most dangerous leading threats for human, according to WHO it can raise the death rate nearly 20%, in 2030. Breast cancer is the one of the threat in women life to cause the death. Digital mammography is an effective method to detect breast cancer. A typical mammogram contain various information that represents tissues, vessels, ducts, chest skin, breast edge, the film, and the X-ray characteristics[1-3]. In mammograms, the objects of clustered masses or lesions, micro-calcifications, distortion are appear in breast architecture. CAD system is developing since last decade to improve the accuracy in detection of cancer. CAD is able to identify the Regions of Suspicion part (ROS); it can make a decision whether a ROS is benign or malignant. The general process of CAD for mammograms refers to image pre-processing, defining ROI, extracting features and classifying a ROI into benign, malignant or the appearances of micro calcifications are small bright arbitrarily shaped regions. The appearances of mass lesions are dense regions of different size and properties, which can further described by circumscribed, speculated or ill-defined. [4, 5]

At present the detection of micro calcifications is still difficult because of their fuzzy nature, low contrast and low distinguish ability from the ROI. The average size is 0.3 mm and micro calcifications are in the range of 0.1-1.0 mm. Cluster masses range is around 1 to 2,5 cm. Sridhar et al.[5] described characteristics of size, homogeneity, position of masses are various pointed out that the main obstacle of mass detection is the great variability of mass appearance with other Abnormalities. Asymmetry and architectural distortion are also hard to detect [6] the shapes, distributions and sizes of micro calcifications are tremendously vary with age. It is difficult to segment micro calcifications because tissues surround them [3]. Masses are groups of cell that are clustered together, and they contain a strong density than the surrounded area. Therefore, the method for detecting all breast abnormalities still is a challenge [5, 6]. The techniques for detection,

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classification and annotation can benefit to the research of computer aided mammography. Researchers are conducted related work for various types of breast abnormalities for more than two decades. Present, segmentation based computer aided detection systems for mammogram both mass and micro calcification is used in clinical routine checkups[6]. For the lesions of breast, [7] presents a tool system in [12], including imaging segmentation of ROI, extracting ROI characterization by means of textural features computed from the gray tone spatial dependence matrix (GTSDM), containing second-order spatial statistics information on the pixel gray level intensity, and classify ROI with neural network. In 2008, Pal et al. used 24 kinds of features for four types of window sizes to detect micro calcification, which resulted in computing 87 features for each pixel. [8, 11]

2. Morphological Filtering Theory

Mathematical morphology is set theory is using in all areas image processing techniques and analysis based on the geometric shape of objects. Structuring element is acting important role, in features extraction, suppressed, or preserved. Morphological filters, consisting the fundamental operations such as dilation, erosion, opening, and closing. These operations are suited for many applications including digitization, enhancement, compression, restoration, segmentation, and description [20].

Morphological filters are functions a nonlinear operations. Morphological dilation is applied to smooth small dark regions. The values of structure elements is positive, the output appears as much brighter. Depending of the shapes and sizes of the structure elements, some of the dark elements on the image are reduced. Erosion is the opposite operation to smooth the low intensity areas. A morphological opening eliminates bright areas in the image that are smaller in size and breaks narrow connections between two bright objects. A morphological closing stores a small area in an image that appears brighter than the surrounding and connects bright objects with little gaps [21, 22]

Consider X is a binary image and let B is a binary structuring element. The AF is defined as an opening followed by a closing or a closing followed by an opening, and is represented as

$$AF_B(\mathbf{X}) = (X \circ B) \bullet B. \tag{1}$$

Another type of AF is defined as

$$AF_B(X) = ((X \circ B) \bullet B) \circ B \tag{2}$$

$$AF_B(X) = ((X \bullet B) \circ B) \bullet B. \tag{3}$$

Iterative application (ASF) is an of $AF_B(X)$ with increasing size of structuring elements, denoted as

$$ASF(X) = AF_B \ (X) AF_B. \tag{4}$$

Let N is an integer and B_N, $B_{N-1}, \ldots, B_1$ are structuring elements with decreasing sizes. The B_N is constructed by

$$B_N = B_{N-1} \quad B_1 \qquad \text{for } N \geq 2. \tag{5}$$

The ASF offers a method of extracting image features hierarchically. The features can be classified into unique layers according with respective to particular structure element.

The structure element sizes of each layer can be applied in many areas; for example, feature classification and recognition

$$(X) \cdots AF_B \ (X), \tag{6}$$

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3. Back-Propagation Neural Network algorithm

A neural network is a general mathematical computing paradigm that models the operations of biological neural systems. As given in the (7) is cumulative equation of back propagation

$$U = \sum_{j=0}^{N} wj + \theta \ . \tag{7}$$

wj are called synaptic weights. The value θ is called the threshold. Weights are applied on each layer of neuron in the form matrix. The values can a feed the error to the input of the network [9, 10].

A neural network is used a two parts, one is a summation unit to compute net functions U. Let us consider the Z is the output is a non linear activation function process the U. The process of the algorithm the output is compared to the desired target consider D an error e is feed back to alter the weights at input level.

Where $x_0 = 1$, $\mathbf{W} = [w_0 \ w_1 \ w_2]$ is the weight matrix, and $\mathbf{x} = [x_1 \ x_2]$ the error back-propagation training.

Begins by feeding all K inputs through the MLP network and computing the corresponding output $\{z(k); 1 \le k \le K\}$. Here we use an initial guess for the weight matrix **W**. Then a sum of the error will be computed as

$$E=\sum[e(k)]^2 = \sum [d(k) - z(k)]^2 = \sum[d(k) - \mathbf{f}(\mathbf{Wx}(k))]^2 \ . \tag{8}$$

4. MIAS database

To evaluate the performance of the proposed approach the mammography image analysis society (MIAS) database is taken into consideration. For experimenting both normal and abnormal region of suspicion is selected. So we classified two parts [24]: The size of each image is 512X512 pixels and it is centre in the matrix. If micro calcifications (MC) are present, centre and radii are applied to a group of s not individually.

The abnormalities in the mammogram are difficult to observe when there is an increment of changes into density tissue

5. Detection of individual micro classifications lesions

The lesion were detect from the dense breast mammogram is given in the block diagram fig2. The Mammograms were taken from MIAS data base. [19]. The digital mammogram pre processing by using morphological filters contains opening closing etc. operations with structure elements [22]. The main advantage of this filter is give a better PSNR value than any kind of filter without any loss of information. Then mammogram is segmented by edge based segmentation method and the edge detected image superimposed on to the original image [19,6]. The segmented image is classified and performance evaluated with error back propagation network algorithm [14-18].Here the proposed method detects the lesions of size between 0.1 to 0.3mm**.**

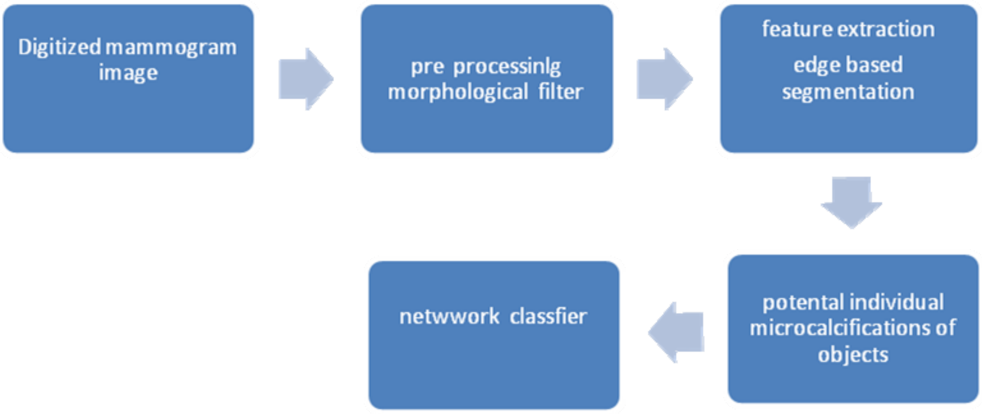

Fig. 2. Block diagram for detection of micro classification lesions

6. Detection of individual clusters classifications

To detect the macro level cluster here detected method is proposed as shown fig3. In this method the process of the detection is performed with morphological curve let transform. Macro level cluster is the ROS extracted from mammogram. ROS is rescaled into the dimensions of 512X512 is given to morphological filter to remove the noise and improve the quality. The clusters is detected apply a morphological operation which marks the area of the ROS and curvelets is extract the area of the marked region. It is been extracted by using morphological curvelet transform [24]. The detected shapes are compared with ground truth shapes. The shapes are represented in a binary format of the two dimensional matrix. Malignancy of the detected shapes is evaluated by the network classifier. [23].

Here we were used error based back propagation network [14-18].the results and discussion is given in the next section.

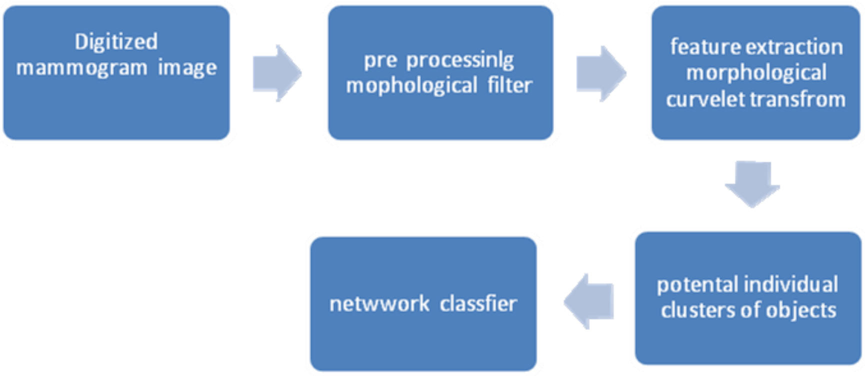

Fig. 3. Block diagram for cluster detection in mammograms

7. Results and discussions

7.1. Evaluation of the micro calcification detection

The programming language used to implement our approach on MATLAB 13 software, performed this test on the MIAS database images.

The first experimental evaluation is related to the ability of the algorithm to detect those mammograms containing micro calcifications. As shown in Figure 4, the best results were achieved when using 100 visual images for describing the different micro calcifications morphology. However, computational dramatically increase at highest data base used here provided a good

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trade-off between performance and feature vector length. we were achieved an area under the ROC of *Az* = 0.922, using again 236 for describing the micro calcifications. This results shows that the algorithm can correctly detect almost all the mammograms containing micro calcifications without a large number of false positive mammograms [11, 12]

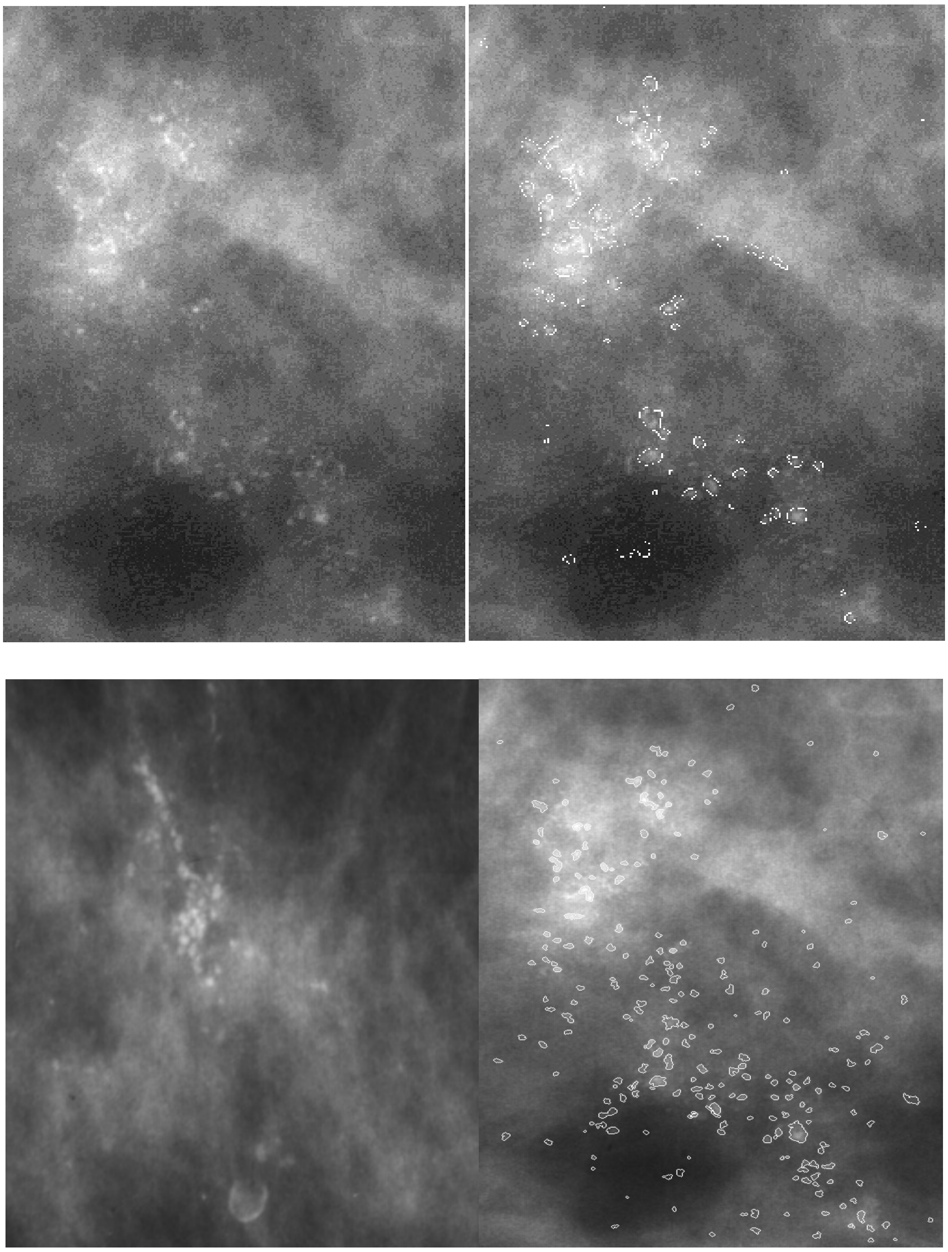

Fig.4. Detection of micro level lesions

7.2. Evaluation of the cluster detection

In the cluster detection approach, the only parameter is the radius of the local neighborhood. We used different dimensions in order to empirically find the best one. In particular, we used 10 different square dimensions as shown in fig 6: from 50 pixels to 500 pixels in steps of 50 pixels The best results were obtained using the kernels of size 100 × 100 and 200 × 200 pixels as shown in fig;7..

Fig. 5. Clustered are various shapes after filtering

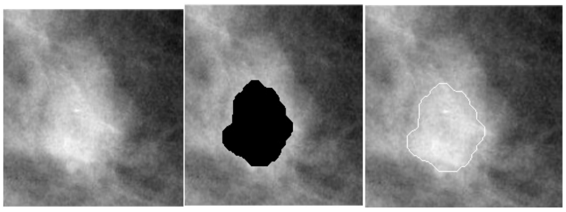

Fig. 6. Cluster malignant and detection of shape

To evaluate the cluster detection we used FROC curves, which are shown in Figure 7.

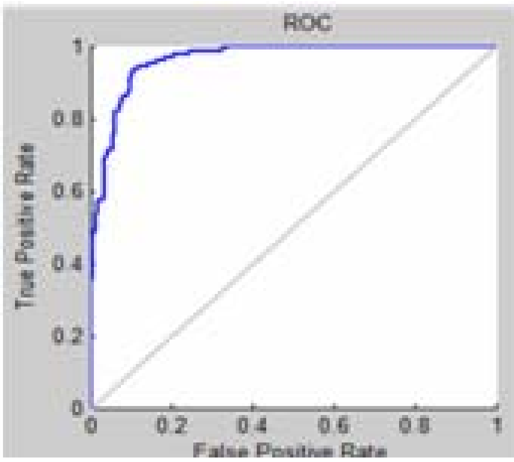

Fig.7. Froc curve testing mammogram

As in the previous experiment, similar results were obtained for the MIAS and the digital databases. to compute the 95% confidence level of the number of false positives per image at a given sensitivity For the MIAS database, at a sensitivity of 82% we obtained a confidence interval of (0.96, 1.73) false positives per image, while at 90% the false positive number per image ranges between (3.23, 5.52). Looking at the results, we noticed that two of the 21 clusters were detected as malignant out of the 100 MIAS suspicious mammograms with very low probabilities; they were located in highly fatty tissue regions.

8. Conclusions

We presented a new breast cancer detection based on mathematical morphology and back propagation neural network algorithm. In this segmentation technique ROS for clusters and micro calcification are concentrated. Detection micro calcification is done through an edge detection based algorithm. This successfully highlighted the micro calcification in between0.5 mm to 2mm.

Clusters are sizes more than 1 cm is detected by using morphological curvelet transform. Detection process consists of preprocessing and feature extraction. Noise removal of the image is obtained by using morphological filter. The segmentation part classified and analyzed by using neural networks. Here we were used a back propagation neural network is used to evaluate the detection. Region of characteristics (ROC) of the method achieved the value which is human feature extraction we obtained mean Az = 0.92, which is slightly lower than the results obtained. The performed experiments have shown the validity of our approach when using to analyzed digital mammograms with dense tissue, the results had obtained the better than exiting method, however time delay of the proposed method is high. Also required a largest MIA's data to analyze the mammogram minimize the further biopsy of the patient.

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