A New False Positive Reduction Method for MCCs Detection in Digital Mammography

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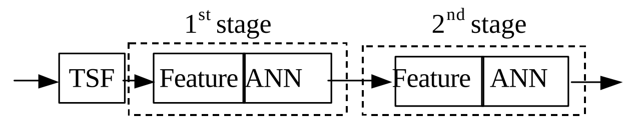
ABSTRACT

A new mixed feature multistage false positive (FP) reduction method has been developed for improving the FP reduction performance. Eleven features were extracted from both spatial and morphology domains in order to describe the micro-calcification clusters (MCCs) from different perspectives. These features are grouped into three categories: gray-level description, shape description and clusters description. Two feature sets that focus on describing MCCs on every single calcification and on clustered calcifications, respectively, were combined with a back-propagation (BP) neural network with Kalman filter (KF) [3] to obtain the best performance of FP reduction. First, 9 of the 11 gray-level description and shape description features were employed with BP neural network to eliminate all the obvious FP calcifications in the image. Second, the remaining MCCs will be classified into several clusters by a widely used criterion in clinical practice, and then the two cluster description features will be added to the first feature set to eliminate the FP clusters from the remaining MCCs. The performance results of this approach were obtained using an image database of 100 real cases of patient's mammogram images in H. Lee Moffitt Cancer Center imaging program [3].

1. INTRODUCTION

Breast cancer is one of the leading causes of cancer deaths among women in the United States [1-2]. A woman has a 12% chance of developing breast cancer and a 3.5% chance of dying from this disease over her lifetime [3]. Therefore, the detection of MCCs has received considerable attention nowadays. Clinically, MCCs are described as the presence of small deposits of calcium (usually less than 0.5mm) arranged in a cluster [2]. They can be found as some poorly defined masses, architectural distortions, asymmetrical structures or as some developing density or isolated ducts. Such diverse descriptions of MCCs provide different approaches to detect MCCs in different computer-aided diagnostic (CAD) schemes. The reported methods include both statistical and non-statistical approaches [3], such as Bayesian classifier, binary decision tree, asymmetry measures and BP neural network. A shift-invariant artificial neural network (ANN) approach has been developed to reduce the FP detection rate of MCCs [4], the feature set they use mainly derived from the spatial domain using raw image data. An improved method was developed using a mixed feature set by neural network with spectral entropy decision algorithm [3]. In this project, by deliberately selecting a mixed feature set that was extracted from the spatial domain enhanced image and the morphology domain segmented image, we developed a multistage mixed feature algorithm using a BP neural network with KF to detect the micro-calcification clusters. Thereby, the sensitivity detection rate of TP has been successfully reached to 97.6% in this study.

The architecture of this new algorithm is shown below:



The TSF is a two-stage symmetrical tree structured nonlinear filter [5] that was earlier reported by our group. The first stage of TSF uses multistage tree structured filter architecture for image enhancement that includes several center weighted median filters as the basic sub-filter blocks. The second stage is a tree-structure wavelet transform that provides further image enhancement and segmentation. The output of this wavelet transform filter is an enhanced and corresponding segmented image. The enhanced image will be used for extracting spatial domain features; the segmented image will be used for extracting cluster description features and morphology domain features for subsequent analysis.

The feature set used in this project includes spatial domain features, morphology domain features, and the cluster description features. The first stage uses 9 features from both spatial and morphology domains, while the second stage includes 11 features which consists of 9 features in the 1st stage plus two cluster description features. The first stage mainly focus on eliminating the most "obvious" FP, which acts as a "coarse" analysis and classification as compared with the second stage's "fine" analysis and classification. The ANN in the figure is a BP neural network with KF that is responsible for processing the extracted feature set in each stage. A corresponding training-testing-erasing cycle was used in each stage for obtaining a better performance of suppressing the FP noises. The mixed feature set using a BP neural network with KF shows a better performance improvement on the TP rate while keeping the same low FP rate.

The motivation of this project is to develop a new FP reduction method in digital mammography. By implementing the newly introduced feature sets of cluster description features and morphology shape analysis features in a multi-stage architecture and using the TSF and BP neural network with KF reported by our research group, we can greatly improve the performance of MCCs detection.

The organization of the rest of this paper is as follows. In Section 2, the feature set used in this project is described and in Section 3 the multistage training-testing-erasing algorithm is presented, which mainly focus on describing the MCCs on single calcification perspective of view and clustered calcifications perspective of view, by using the multistage FP reduction algorithm. Finally "survived" calcification will mainly contain the TP MCCs, which is very important for the MCCs classification procedure. In Section 4, the database used in this project, the experimental results and discussion are presented, followed by the conclusion in Section 5.

2. SELECTED FEATURE SET

Eleven features from spatial domain (spatial description) and morphology domain (shape description) and as well as some cluster description features were used. Features include (a) Average and standard deviation of the gray-levels of foreground in the enhancement image. (b) Average and standard deviation of the gray-levels of background in enhancement image. (c) Average of maximum gradient of boundary pixels. (d) Average of mean gradient of boundary pixels. (e) Cluster region size. (f) Cluster shape rate, (g) Compactness, (h) Moment of region boundary, (i) Fourier descriptor. In all these features, (a) to (d) belong to the spatial domain, (e)-(f) belongs to the cluster description, and (g)-(h) belongs to the morphology domain. These features provided a method of describing MCCs from different perspective of view. By selectively grouping these mixed features into different sets, we can integrate them into different stages of our multistage training-testing-erasing cycle of our neural network to gain the best performance of reducing the FP calcifications.

2.1 Spatial domain features

These features are extracted from the enhanced output image of the previously reported TSF [5]. It includes:

(a) Average gray-level of foreground in enhanced image:

$$Avg_{forground} = \frac{1}{sum(pixel_{foreground})} \sum_{(m,n)\in foregorund} x(m,n)$$

(b) Average gray-level of background in enhanced image:

$$Avg_{backgournd} = \frac{1}{sum(pixel_{foreground})} \sum_{(m,n)\in background} x(m,n)$$

(c) Standard deviation of gray-levels of the foreground in enhanced image:

$$\mathrm{Stdev}_{foreground} = \Big(\sum_{(m,n)\in \mathrm{foreground}} [\mathrm{x(m,n)} - \mathrm{Avg}_{\mathrm{foreground}}]^2 \Big)^{\frac{1}{2}}$$

(d) Standard deviation of gray-levels of the background in enhanced image:

$$\mathrm{Stdev}_{background} = \Big(\sum_{(m,n)\in \mathrm{background}} [\mathrm{x(m,n)} - \mathrm{Avg}_{\mathrm{background}}]^2 \Big)^{\frac{1}{2}}$$

The above four features is based on the fact that the MCCs clusters have apparently different gray-levels compared to the background tissues. By introducing the previous reported results of using the enhanced image to extract the gray-level features [5][3], we can get a better description of these four features.

The gradient operators are represented by a pair of masks H_1, H_2, which measure the gradient of the image u (m, n) in two orthogonal directions. By defining the bi-directional gradients as: $g_1(m, n) = \langle U, H_1 \rangle_{m,n}$ and $g_2(m, n) = \langle U, H_2 \rangle_{m,n}$, then the gradient vector magnitude and direction are given by:

$$g(m,n) = \sqrt{g_1^2(m,n) + g_2^2(m,n)} \qquad q_g(m,n) = \tan^{-1}\frac{g_2(m,n)}{g_1(m,n)}$$

Using the above formula, the segmented image is first screened, labeled all the boundary pixels of each calcification, and then mapped back to the enhanced image to get their boundary pixel gradient. The gradient feature is based on the optimized algorithm, which use an initially given value and initially defined searching direction to find the optimized convergence solution for the problem. The Sobel gradient operator was used for calculating the gradient description features used in this project with the masks defined as:

$$\mathrm{H}_1 = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix} \qquad \mathrm{H}_2 = \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix}$$

(a) Average of maximum gradient of boundary pixels: This is obtained by calculating the gradient of each boundary pixel's 8 connected neighbors and taking the maximum gradient value.

(b) Average of mean gradient of boundary pixels: This feature is obtained by calculating the gradient of each boundary pixel's 8 connected neighbors and taking the average of its neighbor's gradient value as its gradient.

2.2 Morphology domain features

These features mainly focus on the shape description. It is extracted from the segmented image of the TSF filter.

(a) Compactness: $\gamma = \dfrac{(\mathrm{perimeter})^2}{4\pi(\mathrm{area})}$

For a disc, g would be minimum and equals to 1

(b) Moment: For a two-dimensional image f (x, y), the moments m_{pq} of order (p + q) are defined as:

$$m_{pq} = \int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty} x^p y^q f(x,y)dxdy \text{, for p, q = 0,1,2…}$$

and the central moments are defined as

$$m_{pq} = \int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty} (x-\bar{x})^p (y-\bar{y})^q f(x,y)dxdy$$

where, $\bar{x} = m_{10}/m_{00}$ and $\bar{y} = m_{01}/m_{00}$

For a binary image, the above formula can be rewritten as:

$$\bar{m} = \frac{1}{N}\sum_{(m,n)\in\Re}\sum m \text{ , } \bar{n} = \frac{1}{N}\sum_{(m,n)\in\Re}\sum n$$

$$m_{pq} = \sum_{(m,n)\in\Re}\sum (m-\bar{m})^p (n-\bar{n})^q$$

(c) Fourier descriptor: It is a transformation feature for shape representation in digital image processing, which transforms a feature set from time-domain into frequency-domain. First, it transforms the two dimensional image into a complex representation image, of the form $u(n) = (x(n) + jy(n))$, n = 0, 1,..,N-1. Then by using algorithm called "chain code" to trace the outline of the calcification boundary with the fixed $2kp$ period, we can get the Fourier representation of the shape features. As we can see that if we use a fixed period, then calcifications with different areas or same area with different outlined boundaries will have different values of Fourier descriptor. This makes it a very useful shape analysis feature. The mathematical model of the Fourier descriptor is as follows:

$$u(n) \stackrel{\Delta}{=} \frac{1}{N}\sum_{k=0}^{N-1} a(k)\exp\Big(\frac{j2pkn}{N}\Big), \ 0 \le n \le N-1$$

$$a(k) \stackrel{\Delta}{=} \sum_{k=0}^{N-1} u(n) \exp(\frac{-j2pkn}{N}), \quad 0 \le k \le N-1$$

2.3 Cluster description features

Radiologists usually use clusters to classify TP calcifications from the FP calcifications. The cluster description features are introduced for this reason. They are extracted from the segmented image of TSF filter; they mainly focus on describing the MCCs on the TP cluster and FP cluster. This is a different approach from the above gray-level and shape analysis descriptors. The criterion that we use to make a cluster is based on finding a group of 3 to 5 or more calcifications each less than 0.5 mm in size and 5 mm apart in a 1cm^2 screening window [6].

(a) Cluster region size: It is the summation of all the pixel number of the calcifications in the same cluster area.

(b) Cluster shape rate: It is the rate of the summation of the length with the summation of the width of all the calcifications in the same cluster.

Among all these features, the spatial domain features are extracted from the enhanced image of TSF filter, while the morphology domain features and the cluster description features are extracted from the segmented image of the TSF filter. We will group these features into two sets for training the BP neural network with KF.

3. MULTISTAGE FP REDUCTION USING BP NEURAL NETWORK

The BP neural network used is a three-layer feed-forward network with one hidden layer with the feature set described earlier fed to the input layer and the output being an integrated sum of weighted inputs shaped by a sigmoid-like function

$$\text{Output} = \frac{1-\exp(-\sum_i w_i x_i)}{1+\exp(-w_i x_i)}$$

where x_i and w_i are the input and its weight.

Before using the neural network, a group of features were collected as input data and corresponding to every input data, a set of target values were provided as 1 for the TP calcification and 0 for the FP calcification. An experienced radiologist carefully inspected the input data and labeled all the TP and FP calcification spots. The neural network used is based on a previously reported BP neural network with KF [3] that has been proved to provide rapid convergence, low training error and high accuracy. The neural network algorithm used is as follows:

Output layer weight:

$$w_0(t) = W_0(t-1) + k_0(t)(d_0 - y_0)$$

Hidden layer weight:

$$w_j(t) = W_j(t-1) + k_j(t) d_j m_j$$

Kalman gain vector:

$$k_j(t) = \frac{R^{-1}(t-1)x_{j-1}(t)}{b_j + x_{j-1}^T R_j^{-1}(t-1)x_{j-1}(t)}$$

The update equation for the inverse matrix:

$$R_j^{-1}(t) = [I - k_j(t)x_{j-1}^T(t)]R_j^{-1}(t-1)/b_j$$

where I is the identity matrix, x is the input at each layer, d_0 is the desire output, y_0 is the actual output, b_j is the "forgetting" factor, m_j is the convergence rate and d_j is the back-propagation error.

Based on this BP neural network with KF, a multistage algorithm with training-testing-erasing procedure has been developed. In the first stage, 9 of the 11 features were used (except the two cluster description features) to train the neural network. This stage mainly focuses on every single MCCs calcification spot in each image to determine whether it is a TP MCCs or FP MCCs. By using a predefined erasing procedure, we can eliminate all the detected FP MCCs to get a relatively "clean" image for subsequent analysis. The second stage uses all the 11 features to process the "clean" output image of the first stage, by introducing the cluster description features in this stage. All the remaining MCCs in the segmented image are grouped into several clusters and the features are extracted again only from every clustered MCCs by continuing the training-testing-erasing procedure for a second cycle in the clustered region. Here, widely used criterion in clinical practice of 1cm^2 screening window is used to inspect the whole image for making a cluster. A unique labeling number will be given to all the MCCs in the same cluster; all the other MCCs that cannot make a cluster will be erased from the image by the later erasing process. The aim of this stage is to use a cluster description perspective to analyze the remaining MCCs. After this stage, all the FP calcification clusters will be erased from the image. After these two stages, the final "survival" MCCs is almost the TP MCCs.

4. EXPERIMENT RESULTS AND DISCUSSION

The results are based on the USUHS image database in H. Lee Moffitt Cancer Center imaging program, which contains 100 real cases of patient's mammogram images, among them, we use 63 images, 84 clusters as our training data, use 65 images, 100 clusters as our testing data. The training data is sent to TSF with enhanced and segmented images as its output and all of it's TP and FP MCCs spots are then labeled by an experienced radiologist providing the target value for the training. Fig. 1 is the output image of TSF. Figs. 2 and 3 show the result of each stage of the multistage FP reduction algorithm, respectively. Fig. 4 is the result of the previously reported TSF and BP neural network with KF [3]. Our testing is based on the following two steps:

4.1 The first testing stage

Nine features, which cover spatial and morphology domains, are extracted from the enhanced output image or the corresponding segmented image to provide the input data for the neural network. The purpose of this stage is to focus on every single MCCs spot and to eliminate all the "obvious" FP MCCs while keeping all the TP MCCs intact. We use a strategy that allows some FP noise MCCs to be falsely treated as the TP MCCs so that it will remain in the output image of this stage. By doing this, we can almost keep all the TP spots intact for the subsequent analysis. This strategy allows selecting specific threshold to erase the FP MCCs in our testing data. Since all the MCCs spots in our training database are already labeled, it is possible for us to control the convergence rate and to get the optimized weights for our BP neural network during the training process. This proved to be an effective method in our study. By setting different threshold on the final output result, we can selectively control by keeping "all" the TP MCCs while effectively eliminating most of the "obvious" FP MCCs. Fig. 2 shows the resulting image output for this stage.

4.2 The second testing stage

In this stage, we use all the 11 features to classify the TP MCCs clusters from the FP MCCs clusters in the test database. As we already label all the TP and FP dusters in our training database, it is possible to control the process for classifying all the TP MCCs from all the FP MCCs in our test data. This process is also controlled by adjusting the BP neural network convergence rate in our training data for providing a well-trained neural network for testing. Fig. 3 shows the resulting output after the second stage.

We compared the performance of the newly introduced multistage FP reduction module with the previously reported TSF and BP neural network with KF. As we can see from Figs. 3 and 4 that the proposed architecture and the feature set provides a very promising performance in FP MCCs reduction. Fig. 4 has some apparently FP MCCs clusters that have been successfully erased by the new method (Fig. 3). By carefully inspecting the original image (Fig. 1) we can see that the MCCs are very loosely spread in the whole mammogram. They have different shape formation and also tend to gather into different clusters. These are two different aspect features of MCCs in a mammogram. The earlier approach only use a combined single MCCs description features to analysis the whole MCCs set and faces a problem of not being able to separate those FP MCCs spots with a very similar shape features in a FP cluster region. By using the new multistage module, we can erase those FP MCCs and FP clusters residing in the image separately.

5. CONCLUSION

The newly developed mixed feature multistage FP reduction scheme can effectively erase most of the FP MCCs. By using the FP reduction scheme, we can generate relatively "clean" segmented image with most of the FP MCCs eliminated for intensive analysis by radiologists. FP reduction is an important and necessary step for the detection of MCCs in digital mammography. The mixed feature set provided two different views of study of the MCCs and the BP neural network with KF offered a flexible, accurate solution to the FP reduction problem. A FP detection rate performance improvement of 42% was achieved by the proposed method described in this paper when compared to the earlier reported method. False positive MCCs reduced from 5/image to 3.15/image. Our approach shows promising results that deserve further investigations.

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Fig. 1

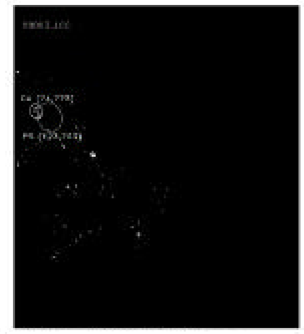

Fig. 2

Fig. 3

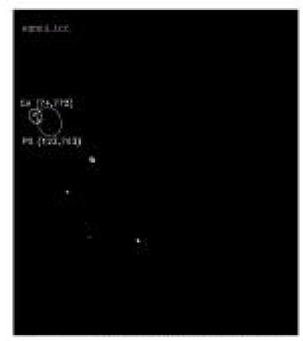

Fig. 4

Fig. 1 TSF Enhanced Original Image
Fig. 2 Output of the Old Method
Fig. 3 Output of First Stage of the New Method
Fig. 4 Output of Second Stage of the New Method
Old Method: TSF and BP Neural Network with KF
New Method: Multistage FP Reduction Enhancement of the Old Method

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