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# A Hybrid Neural System for ROI Selection in Microcalcification Detection

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**Abstract –** Microcalcifications appear as small bright spots varying in size and shape in mammographic images and they are usually grouped into clusters. An image can contain more than one cluster but the area of the clusters is still far smaller than the area of the breast. The aim of ROI (regions of interest) selection is to detect suspicious areas for further analysis. We present here an algorithm for ROI selection consisting three steps; image enhancement, feature selection and classification. The classification step of the proposed algorithm is performed by a hybrid neural system which uses supervised and unsupervised networks.

## 1. Introduction

Breast cancer is the most common form of cancer among women. According to statistics, 8% of women will develop it in her lifetime. Thanks to recent advances in medicine, there are effective methods in the treatment. The sooner the illness is detected the more effective the treatment is. If detected early, the five-year survival rate exceeds 95%. Mammography is one of the most effective ways for early detection and the early signs of cancer in most of the cases are clustered microcalcifications. In a mammographic session, four x-ray pictures of the two breasts are taken (typically craniocaudal (CC) and mediolateral (ML) views) [1]. Mammography is used to detect abnormalities and judge their severity; to differentiate benign and malignant cases. One of the most important abnormalities are microcalcifications.

In microcalcfiicaton detection, the selection of ROIs is a focal problem as it can improve the performance of the algorithm and it is equally important that it can decrease the number of false positive detections which is a growing problem in CAD systems.

In this paper we present a method that selects ROIs which then can be used as inputs for a microcalcification detections algorithm. Microcalcification detection algorithms use different approaches to sign microcalcifications [2, 3], but most of them first try to select suspicious regions which then are further analysed for the presence of microcalcification clusters. The presented algorithm uses a simple scheme for detecting ROIs; the steps are image enhancement, feature extraction and classification based on the features. In feature extraction we extracted two sets of features; one set is based on a statistical texture based method, the SRDM method [5]. For classification, we propose a hybrid neural system which uses supervised feedforward neural networks, and unsupervised self-organized maps. Using a hybrid system is motivated by the idea of generating and combining classifiers in such a way that the individual classifiers themselves provide (at least) better solutions than simple guessing and at the same time they make their errors in different parts of the input space [4].

This paper is organized as follows. Section 2 introduces the image enhancement and feature extraction steps. In Section 2 a review of the SRDM method [5] is also given. Section 3 presents the hybrid neural system for classification, and then we evaluate our algorithm in Section 4 through experiments and present the results. Section 5 concludes this paper and discusses future work.

## 2. Image enhancement and feature extraction

### 2.1. Image enhancement

The first step in our algorithm is image enhancement. In this step the input ROI is first filtered with an averaging filter then the filtered image is subtracted from the original one. For every pixel, therefore, the following neighbourhood operation is carried out,

$$S_{diff}(x,y) = S(x,y) - \frac{1}{n}\sum_{i,j\in W} S(i,j), \qquad (1)$$

where $W$ is a window with size $n$ centered around the pixel $(x, y)$ with intensity $S(x, y)$. An input ROI and its enhanced version are shown in Fig 1.

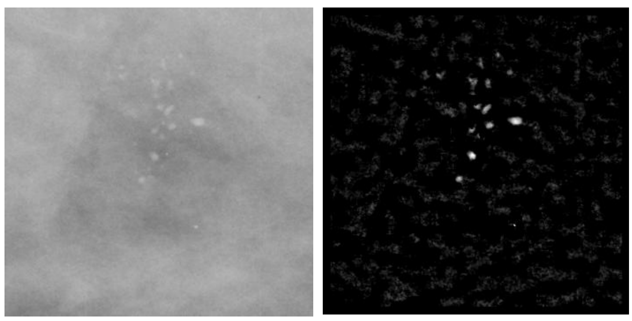

Fig 1. An input ROI (left original, right enhanced)

### 2.2. Feature extraction

*2.2.1. Gray-level features*

The next step after image enhancement is feature extraction. In this step, we extract three features from the ROI as described below and four additional features based on the surrounding region dependence method [5].

First for each ROI two sums are computed. First summing the intensity values by rows and then summing them by columns. That gives us two vectors (e.g. vertical and horizontal sums),

$$F_1(r) = \sum_c S(r,c) \quad (2)$$

$$F_2(c) = \sum_r S(r,c) \quad (3)$$

Then by using a feature selection algorithm we selected three features which were composed from the statistical properties of $F_1$ and $F_2$ (standard deviation and mean).

*2.2.2. SRDM features*

Four additional features are extracted from the ROI based on the surrounding region-dependence method (SRDM). The method is a statistical texture based method and it was proposed especially for microcalcification detection [5]. In this section, we give a brief overview of the feature selection process based on this method.

For every image pixel, we define three windows which give us two regions *R1* and *R2* (see Fig 2).

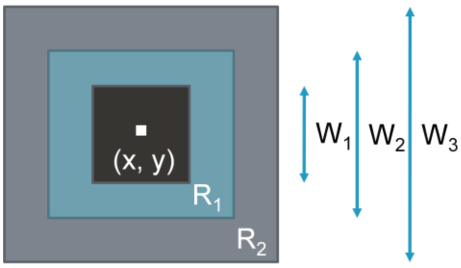


Fig 2. Surrounding region

We can count those pixels in each surrounding regions whose difference is greater than the threshold compared to the central pixel,

$$c_{R_1}(x,y) = \#\{(k,l) \mid (k,l) \in R_1 \wedge [S(x,y) - S(k,l)] > q\} \quad (4)$$

$$c_{R_2}(x,y) = \#\{(k,l) \mid (k,l) \in R_2 \wedge [S(x,y) - S(k,l)] > q\} \quad (5)$$

Using the counters introduced above we can define a matrix depending on the threshold q,

$$M(q) = [\alpha_{ij}], \quad 0 \le i \le m, 0 \le j \le n \quad (6)$$

where the $\alpha_{ij}$ a element gives the number of those pixels where the inner counter (e.g. the number of pixels in region $R_1$ whose difference to the central pixel is greater then the threshold) equals $i$ and the outer counter equals $j$,

$$\alpha_{ij} = \#\{(x,y) \mid c_{R_1}(x,y) = i \wedge c_{R_2}(x,y) = j\}, \quad (7)$$

where m and n are the number of pixels in regions $R_1$ and $R_2$. Let N be the sum of the elements of the matrix $M(q)$, and $r(i,j)$ is the reciprocal of the elements,

$$N = \sum_{i=0}^{m} \sum_{j=0}^{n} \alpha(i,j) \quad (8)$$

$$r(i,j) = \begin{cases} \dfrac{1}{\alpha(i,j)}, & \text{if } \alpha(i,j) > 0, \\ 0, & \text{otherwise} \end{cases} \quad (9)$$

Then four features that it is suggested by [5] are extracted from the above defined matrix which are shown below, for more details refer to [5],

1) horizontal weighted sum

$$HWS = \frac{1}{N} \sum_{i=0}^{m} \sum_{j=0}^{n} i^2 r(i,j) \quad (10)$$

2) vertical weighted sum

$$VWS = \frac{1}{N} \sum_{i=0}^{m} \sum_{j=0}^{n} j^2 r(i,j) \quad (11)$$

3) diagonal weighted sum

$$DWS = \frac{1}{N} \sum_{k=0}^{m+n} k^2 \left( \sum_{\substack{i=0 \\ i+j=k}}^{m} \sum_{j=0}^{n} r(i,j) \right) \quad (12)$$

4) grid weighted sum

$$GWS = \frac{1}{N} \sum_{i=0}^{m} \sum_{j=0}^{n} ij\, r(i,j) \quad (13)$$

We used the features presented here for classifying each input ROI. The classification is performed by a hybrid neural system described in the following section.

### 3. A hybrid neural classifier

The past decades have seen the success of ensemble methods, multiple classifier systems, mixture of experts both in theory and in applications [6, 7, 8]. Algorithms like boosting and bagging and their variations are used successfully in solving many problems, however, it is shown that sometimes these approaches cannot increase the performance. We conducted several pilot experiments with bagging and boosting but they could not increase the performance in our case. Therefore we chose a different approach to combine classifiers which is presented in the following.

The motivation behind the proposed system is to create diverse networks that give good results individually but make mistakes for different input patterns [4].

The proposed system is shown in Fig. 3.

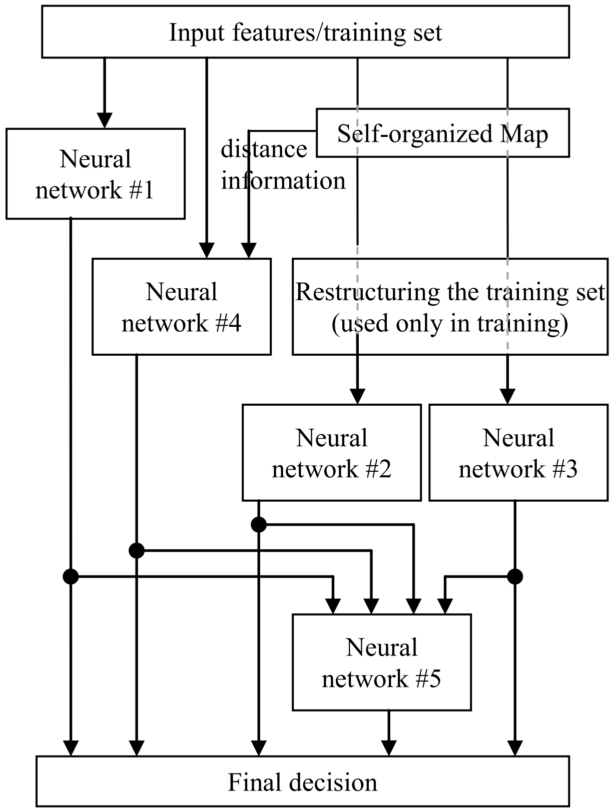


Fig 3. A hybrid neural system for classification

The proposed hybrid neural system consists of supervised and unsupervised neural networks to solve the classification problems. All of the supervised networks are feedforward neural networks (*Neural network #1 - #5* in Fig 3.) with one hidden layers that consists of eight hidden neuron. We used tangent hyperbolic nonlinearity in the neurons. The unsupervised network currently is a simple self-organized map (SOM), which is used to generate new features for other networks and to divide the original training set in order to create new training sets. The detailed description is given below.

The first neural network (*Neural network #1* in Fig 3) is trained using only the features described in Section 2. This network is fully trained therefore it is considered to represent the original problem as it is therefore it can be used for classifying an input ROI in itself.

The self-organized map (SOM) is used to form two clusters in the input space based on the input features. The choice for using two clusters is motivated by the original problem that is to classify an input ROI to either positive (microcalcifications are present) or negative (microcalcifications are not present).

By clustering the training set using the SOM, we get two groups of samples with each group containing samples from both the positive and the negative classes. We can use these groups of samples as new training sets.

This step is depicted as restructuring or splitting the original training set in Fig 3. Two feedforward neural networks (*Neural network #2* and *Neural network #3*) are then trained using the new training sets. The motivation for this step is to create classifiers which represent the problem in a different way than *Neural network #1*. As the clusters created by the SOM basically are subsets of the original training set we can consider these networks as to represent the original problem, though they have certainly less information about it.

For each sample the SOM measures the distance from the cluster center. The measured distance can be considered as a feature describing that certain sample. This motivates the use of the fourth network (*Neural network #4*) which is trained using the original input features extended with the distance of the samples from the cluster centers measured by the SOM.

Finally we have a fifth network (*Neural network #5*) which can be considered as a network trying to learn from the mistakes of the other networks and this is the motivation for using this network as well. In this case we create a problem as to learn those output combinations of the four other networks where they make a mistake. Therefore the inputs of this network are simply the four outputs of the other networks while the targets are the same as for all of the networks (one for a positive ROI and minus one for a negative ROI).

The final decision is the combination of the outputs of the five networks which is currently a simple averaging operation. Note that for this step one could use a voting procedure or other means to compute the final output.

## 4. Experiments and results

For the experiments, 100 positive and 100 negative ROIs were extracted from images of the DDSM database [9] 256x256 pixels each at 50μm resolution. In the experiments, we used a 10-fold cross-validation scheme in order to determine the optimal values of the parameters ($w_1$, $w_2$, $w_3$, $q$ for the SRDM method) and to measure the performance of the system. As said before each neural network had one hidden layer with eight neurons and with tangent hyperbolic nonlinearity. The networks were trained using the RPROP algorithm [10]. For the training cycles we set 2500 using validation. The parameters of the SOM are the learning rate, the number of epochs and the width of the Gaussian neighborhood function. The number of epochs was set to 5000, while the other parameters set to be decreasing as the learning goes starting with a kernel width of 1 and a learning rate of 0.8. In pilot experiments the SOM seemed to be fairly robust to the change of the above parameters.

We conducted experiments using several different settings for the size of the windows ($w_1$, $w_2$, $w_3$ see in Fig. 2.) and for the value of threshold $q$ of the SRDM method.

The performance was measured by the area under the ROC (Receiver Operating Characteristic) curve. Some of the best results with different settings of the above mentioned parameters for the SRDM method are shown in Table 1. The results are given for the presented system (the rows with the *hybrid* title in Table 1) and for a comparison the results reached using only one neural network (namely *Neural network #1* in Fig 3.) for classification are also given. The corresponding ROC curves for the best results regarding the single classifier (as original) and the hybrid classifier are shown in Fig 4.

Table 1. Results of the ROI selection algorithms

| Method | $w_1$ | $w_2$ | $w_3$ | q | $A_z$ |
|---|---|---|---|---|---|
| single network | 3 | 5 | 9 | 8 | 0.974 |
| single network | 3 | 7 | 11 | 9 | 0.958 |
| hybrid | 3 | 5 | 9 | 8 | 0.983 |
| hybrid | 3 | 7 | 11 | 9 | 0.97 |

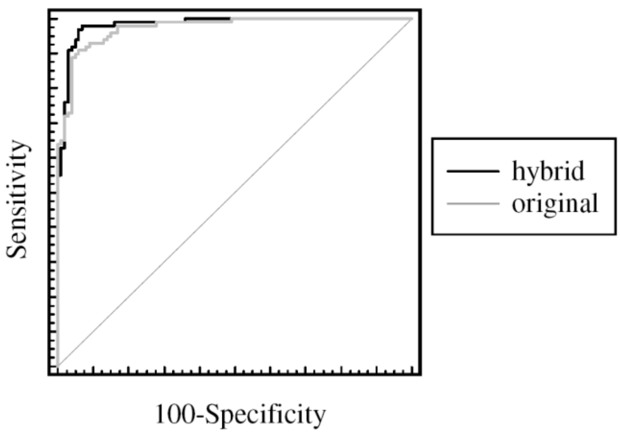


Fig 4. ROC curves for the best results

## 5. Conclusions and future work

The results show two important things to mention in the first place. The first is that the proposed method for ROI selection is viable and can be used as a part of a complex system for microcalcification detection. However, one part of future work has to be to conduct more experiments on larger datasets regarding the problem of ROI selection. The statistical analysis of the given results shows that there is a significant difference between the results reached by the proposed hybrid classifier compared to a single classifier at the 92% level (the p-value is 0.08) but the number of samples is insufficient to prove a significant difference at least at the 95% level.

The second part is a more thorough analysis of the proposed hybrid classifier. For example there is a possibility of using the SOM to select from the networks (network #2 and #3 in Fig 3.) instead of using both.

More importantly, since the proposed hybrid classifier does not depend on the problem at hand it can prove to be useful as a general approach solving other classification problems as well. It is part of the future work to find out whether it is a viable approach for other classification problems or not.

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