Detection and evaluation of breast tumors on the basis of microcalcification analysis

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Abstract. Long-term studies on the possibilities of aiding breast cancer diagnostics with the use of artificial neural networks supported by promising results led the authors of this paper to take up another challenge, the aim of which was localization and classification of microcalcifications. The evaluation of mammographic images by a specialist is not easy, and often ambiguous. Microcalcifications possess 'encoded' significant diagnostic value while having a small size and low contrast. A large number of papers indicates that information included in mammogram can be the basis for extracting the features of microcalcifications and their satisfactory classification with the use of artificial neural networks [9, 10, 12, 13, 14, 15, 16, 19, 20]. Detection of microcalcifications is usually realized in two stages, i.e. by the analysis of mammographic image what results in defining microcalcifications concentration and then by trying to evaluate the degree of their malignance. The paper presents the results of research undertaken in order to evaluate mammograms in terms of detecting places of occurrence and evaluate the degree of their malignance. The evaluation took place on the basis of the analysis of mammographic image with the use of two types of neural networks: feed forward multi-layer MLBP networks and Fahlman networks.
Keywords: microcalcifications, extraction method, segmentation method, binarization method, Fahlman neural network, MLBP neural network

1. Introduction

Studies conducted up to now in the field of supporting breast cancer diagnostics concerned two most significant issues, i.e. detection support and the degree of tumor's malignance, and the classification of microcalcifications with the use of artificial neural networks.
In such studies the most important task to solve was preparing processing methods enabling for obtaining proper feature vectors from mammographic images, constituting coded information describing given medical cases. Principal proceeding methods were taken into consideration, such as image segmentation and binarization [16] and extraction of features from the so-called region of interest [17]. The first step of the examination was implementing image segmentation method, then

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image binarization and global analysis (line summing algorithm) [22] and finally region analysis (ROI) based on paper [17].

In [22] the described methods, as well as the results of the studies were presented in natural order of their occurrence. At the same time, another modifications of the proceeding methods led to the improvement of the results and achieving better results. Neural networks were decision elements in diagnostic software. For their evaluation we applied the methods of generalization, i.e. cross validation.

Acknowledging numerous studies [1, 2, 3, 4, 6, 7, 8, 16, 17, 21, 23], methods and obtained results [13, 22], another studies were undertaken aiming at trying to evaluate mammograms in terms of microcalcification localization and the degree of their malignance. The evaluation was performed on the basis of mammographic image analysis with the use of two types of neural networks: MLBP and Fahlman networks [5, 11, 18].

2. The algorithm of identification of microcalcification localization.

Difficulties with unambiguous evaluation of microcalcifications provoked dividing works into 2 stages:

- stage I – identifying the localization,
- stage II – evaluation of the degree of microcalcification malignance.

The algorithm of detection and classification of microcalcifications was divided into the following steps:

1. Loading a digital form of mammogram.
2. Putting segments of a given size on mammographic image.
3. Determining features for the image segments.
4. Automatic selection of segments containing microcalcifications.
5. Determining additional features for segments selected in step 4.
6. Automatic classification consisting in the evaluation of the degree of microcalcification's malignance.

Each mammogram was divided into square fields, the size of which depended on the size of the analyzed image and analyzed objects and was accepted by a person conducting the examination. Two sizes of networks were adopted: 32x32 (fig. 1) and 64x64 pixels. Examination was carried out for a greater number of segments, but we intentionally ignored their interpretation due to small differences in their results.

Having known the description of each mammogram it was possible to specify the condition of a particular segment (field). We took up a description in such a way that if a certain field included microcalcification (fig. 1a) [10], the condition of such field was regarded as positive and the value equal to 1 was adopted to describe the features of the vector. When no microcalcifications were found, the condition of the segment received the value equal 0 (fig. 2).

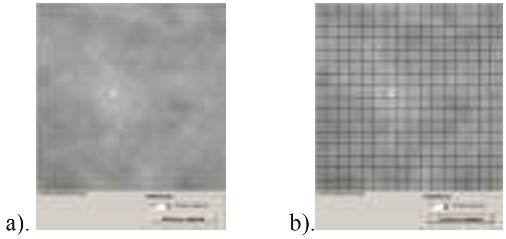

Fig. 1. The field of mammogram of 512x512 pixels size containing microcalcifications a) original image b) image with a chart of fields

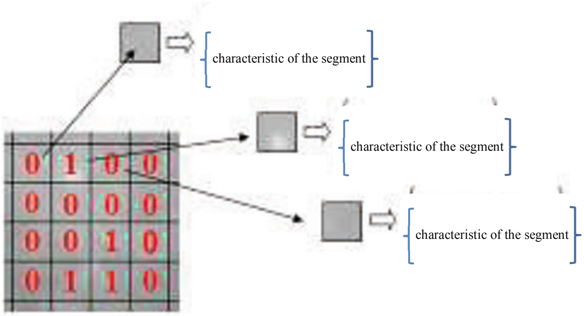

Fig. 2. Segments with the state of activation 0 – negative, 1 – positive

The experience from research on parameterization and evaluation of mammographic images allowed to make use of the previously developed parameters, expanded by new features, for the purposes of identification and evaluation of microcalcifications. For each marked field, the value of the following parameters were calculated (defined in previous research): V – variance, CV – variance coefficient, LFP – longitudinal Fourier power spectrum, AFP – angular Fourier power spectrum [17] and parameters [21, 23] originally proposed for microcalcification detection:

- MG – matrix of the image gradient – describing the difference in the degree of grey of the pairs of pixels adjoining the examinedpixel or located in a distance d from them

$$G_{i,j} = \sqrt{\left(\left(x_{i+d,j} - x_{i-d,j} \right)^2 + \left(x_{i,j+d} - x_{i,j-d} \right)^2 \right)} \tag{1}$$

- SG – sum of the image gradients – describing the sum of the differences of the degrees of grey for the pairs of pixels distant for a maximum distance d

$$SG = \sum_{i,j} G_{i,j} \tag{2}$$

- MKG – angular matrix of image gradient – describing the differences of the degrees of grey of the pairs of pixels adjoining the examined pixel or distant from it by a distance d, located on the sections at the angle of: α: 0-180°, 45-225°, 90-270°, 135-315°.

$$G_{i,j(\alpha)} = \sum_{\alpha} \sqrt{\left(\left(x_{i+d,j} - x_{i-d,j} \right)^2 + \left(x_{i,j+d} - x_{i,j-d} \right)^2 \right)} \tag{3}$$

- GM – average gradient

$$GM = \frac{1}{m}\sum_{i,j} G_{i,j(\alpha)} \tag{4}$$

- MAX – maximal value of the degree of grey in the segment
- MIN – minimal value of the degree of grey in the segment

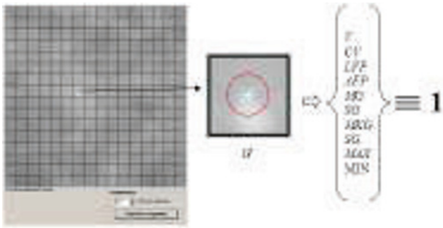

Fig. 3. The pattern of determining the features of mammographic image.

Parameterization of mammographic images carried out this way, together with linking them to medical diagnosis will constitute input sets to the neural networks. During the examination, the evaluation of the size of the feature vector was carried out, as well as its influence on the results obtained with the use of artificial neural networks.
The following sets of features were applied for teaching neural networks [22]:

- V, CV, MAX, MIN
- V, CV, LFP, AFP, MAX, MIN
- V, CV, LFP, AFP, MG, SG, MAX, MIN
- V, CV, LFP, AFP, MG, SG, MKG, GM, MAX, MIN

The best results were achieved for 10-elements vector. The accuracy of localization of microcalcifications was higher for 13% from the weakest result obtained from 4-elements vector of the parameters.

3. The results of identifying the localization of microcalcifications.

The obtained results of the accurate identification of about 92% of microcalcifications and about 90% segments with no microcalcifications, may be considered as very promising. About 5000 segments of different structure were analyzed.
The tools implemented for finding the localization of microcalcifications were Fahlman neural networks [5] and MLBP neural networks [11]. Better results were given by Fahlman neural networks method. It was probably caused by the fact that Fahlman neural network creates architecture individually, what means that during constant updating of the weight, the algorithm automatically analyzes the abilities of generalization of networks and decides on the necessity of adding a hidden neuron. In the case of MLBP network, the architecture is constant. The process of teaching the network consisted in adjusting to patterns the pairs of input vectors containing

features calculated from the segments. In the case of testing the network, for test segments and their features, a result of network was generated, following from the values of test parameters and the importance of networks trained in the process of teaching.

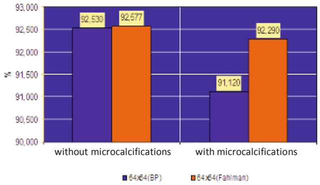

Fig. 4. Comparison of the average results for segments of 64x64 pixels.

4. Application of artificial neural networks in microcalcifications classification.

For the evaluation of the degree of malignance, the same method of research was used due to which the localization of microcalcifications was identified. From among all mammographic images we had to our disposal, 100 segments were chosen with malignant microcalcifications – described in the paper as MZ and 100 segments with benign microcalcifications, called MŁ. The set of 200 segments constituted a training base for neural networks. For testing network and the evaluation of the degree of microcalcifications' malignance, we also chose additional groups of segments of 100 each, containing particular types of microcalcifications. For the evaluation of the degree of malignance we subjected for the analysis of microcalcifications' shape, their number and outlines. As a result of such proceeding method, the feature vector was enriched by additional parameters appointed from binary image.

As a result of preparatory work we obtained a binary image containing microcalcifications (fig. 5.). This form of image allowed for designating additional parameters necessary for the evaluation of the features of microcalcifications' shape.

a). b).

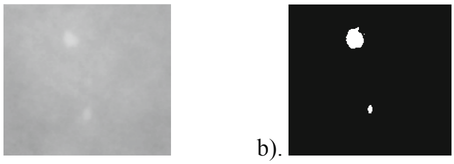

Fig. 5. a) original image and b) its bit map

In the further part of the studies the features were determined which were then introduced into neural network and paired with the appropriate conditions: 0 or 1. Values 0 and 1 corresponded to the conditions of microcalcifications: 0 – MŁ, 1 – MZ. Verification of microcalcifications was carried out by specialists.

For the purposes of describing microcalcifications, each feature vector (V, CV, LFP, AFP, MAX, MIN) described earlier was enriched by the following values:
LK – the number of microcalcifications concentrations
ZM – the outline of microcalcifications (0 – smooth/even, 1 - irregular)
LMK – the number of microcalcifications in a cluster

5. The results of microcalcifications classification.

The results indicate that the number and type of features are of a great significance in the process of microcalcifications evaluation. When classifying such features as: variance, variance coefficient, variance of an average, the degree of minimal and maximal grey – the accuracy of diagnosis is the lowest. Together with the increase of feature vector by angular and linear Fourier power spectrum, the accuracy of BP network grew to over 70%. Whereas a full set of features for network training, increased the accuracy to about 80%. It needs to be emphasized that such parameters as the number of clusters, microcalcification outline, the number of microcalcifications in a cluster, minimal and maximal degree of grey, have a significant impact on the accuracy of microcalcifications' evaluation.
Summarizing, it needs to be stated that as a result of the studies, max. 84% accuracy was achieved for benign microcalcifications and 82% accuracy for malignant microcalcifications. These results were given by Fahlman networks. The studies confirmed previous conclusion indicating that Fahlman neural network is a more effective tool than MLBP.

Feature vector	benign microcalcifications	malignant microcalcifications
V, CV, MAX, MIN.	70%	69%
V, CV, AFP, LFP, MAX, MIN.	75%	76%
V, CV, AFP, LFP, LK, ZM, LMK.	72%	74%
V, CV, AFP, LFP, LK, ZM, LMK, MAX, MIN.	84%	82%

Table 1. The results of the studies for Fahlman networks.

6. Summary.

Studies on the application of artificial neural networks into the analysis of mammographic images in terms of the evaluation of microcalcifications, realized two aims. The first and most important one was preparing a mechanism equipped with artificial neural networks, which was able to locate the places of microcalcifications' occurrence. The second aim was trying to evaluate the places containing microcalcifications in terms of the evaluation of the degree of their malignance.

Mammographic images may be a source of information for diagnostic tools, such as neural networks, through its appropriate parameterization. Due to graphic features of such small objects, the evaluation of the condition of the microcalcifications is a very difficult task. Too little differences in the degrees of grey, together with very small sizes and unclear shapes, are the basic problem in their appropriate evaluation. These problems can be solved by a computer system making use of artificial neural networks. The accuracy of microcalcifications localization of about 90% and their evaluation at the level of 80% absolutely proves it. It has to be added that it was carried out by a system constructed on the basis of MLBP neural network and Fahlman neural network models, the latter demonstrating better abilities of generalization.

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