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COMPUTER ANALYSIS OF THE MAMMOGRAMS ORIENTED ON BREAST CANCER DETECTION

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Abstract: The aim of our study is to create a computer diagnostic system (CDS) for breast cancer (BC) recognizing.

As a software diagnostic tool we have used Fahlman's cascade correlation neural network (FNN).

The FNN was trained by the vector of features – parameters extracted from mammographic images of healthy tissue (H), tissue with benign (BT) and malignant tumour (M).

To prepare digital data for the NN new, original methods of transformation the mammograms were proposed: Algorithm of Summing up the Rows (ASR) operating on the binarized picture, and analysis of extracted features from Region Of Interest (ROI).

There were lots of parameters optimized in previous research; in this work we present discussion of the level of image binarization in ASR method, and discussion of shape, size and number of analyzed features in ROI method.

As the input data for neural network decision making system we have used six parameters calculated from a region of interest (ROI method), and four parameters calculated by the "summing up the rows algorithm" (ASR). We have used all mentioned parameters to create the best combination of features and find the best representative vector, and get the highest correctness of recognition.

The final diagnostic system could us obtain correctness of the mammogram interpretation about 92% for healthy tissue, 89% for benign and 91% for malignant tumors.

Keywords: Breast cancer, feature extraction, neural network

1. INTRODUCTION

Three years of research on computer interpretation of mammographic photos led us to the point that the most important problem is the way of preparing digital data for desision making system. We have used segmentation method (SM)[1], and then two kinds of feature extraction methods algorithm of „summing up the rows" on binarized mammogram (ASR), and the method of extracted features analysis in the region of interest (ROI)[2].

The research with the SM method is finished, because of not satisfactory results. The method allowed only for simple healthy – non healthy diagnosis, contrary to ASR and ROI methods where we could distinguish different kinds of pathologies. These last two methods are still under development, even though obtained till today results are much better. We decided to optimise some parameters, hoping that finally correctness of diagnosis improves. Having many calculated vectors of features extracted from mammograms we resolved to define the best.

The database, used in the experiment, consisted on 600 mammograms described correctly by the medicine doctors. About 400 pictures we have got from the educational database from Marsden Hospital in London available by the Internet, and 200 has come from Bródnowski Hospital in Warsaw. These images have been prepared for the analysis by our team. The results of the computer diagnosis have been evaluated according to classic cross-validation method.

2. METHODS

a. Computer diagnostic system (CDS)

The set of mammographic pictures was scanned and preliminary transmitted to the workstation. We have decided to resize the resolution of images into 400 x 300 pixels with written in 8-bit depth of grey scale. After that we could use two developed by us methods of digital images transformation for acquire characteristic parameters.

First proposed method is ASR (algorithm summing up the row). The fundamental parameter of the mammogram conversion in ASR method is image binarization threshold, called also "the level of the healthy tissue".

In the experiment for the different levels of the threshold from range 140-180 (in grey scale), we have transformed mammograms and have calculated proposed by us parameters. Then we check our diagnostic system built on the Fahlman's neural network (FNN). For the system estimation we have used 6-fold cross-validation on whole available database (consisting of over 600 mammograms). After that we conducted the binaryzation with the best bottom threshold and then "summed up the rows" of pictures acquired this way. We summed up the "zero or one" pixel values in rows and cross out the characteristics of binaryzed images (Fig.1.). From the analysis of the characteristics we have obtained such parameters as:

- number of local minimum (NLM),
- level of the maximum (LM)
- number of symmetrical points (NS)
- number of unsymmetrical (NUS) points.

All mentioned above parameters were computed for the images binarized with threshold equal 165. For this "level of the healthy tissue" determined parameters were the most representative for different medical cases. Thanks that we have got four features to CDS.

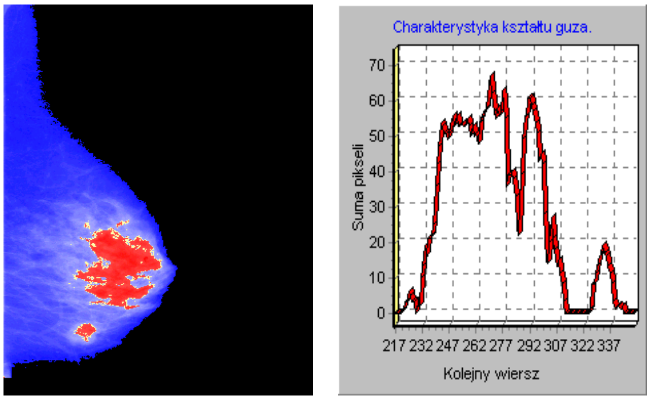

Fig. 1. A nipple with a malicious change and its characteristic.

Second developed and used by us method was the modified ROI method [3]. In our system we freely choose a region of interest (ROI) in the displayed image and we compute for the analysis six variables. We have decided to analyse the same variables like in paper [4], i.e.: variance, variance coefficient, angular Fourier power distribution, longitudinal Fourier power distribution, contrast parameter and variance of the average.

All assumed parameters are very sensitive on changes of the shape, size and fulfilment (brightness of the inner part) of the picture. In our preliminary research we have used one big rectangular region ROI for each analysed picture (as it is shown on Fig.2.a. Development of the research led us to the modified ROI method, which relies on the change of the shape of region (from rectangular to circle), its size and position of the centre. Schematically it is shown on Fig.2.b.

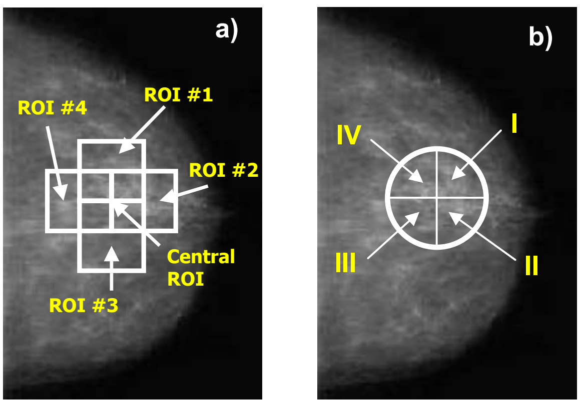

Fig. 2. Arrangement of the rectangular ROI region a); circle four-quadrant ROI region b)

Because of the same dimensions and resolution of mammograms as the measure of the region radius we assumed pixel. In experiment we have used the same diagnostic system built on FNN, but we could build much bigger database. It was possible because the centre position has been arbitrary set by the operator so we could multiply the number of analysed images. The way of the diagnosis correctness estimation was the same as above.

After that we could check our FNN decision making system, and could diagnose the breast cancer on database consisted of about 1500 transformed mammographic images.

b. Fahlman's Neural Network (FNN)

The neural network, we have used in our research as a diagnostic tool, was Fahlman's cascade correlation neural network [5]. The most important advantages of Fahlman's NN are as follows:

- open architecture, adapting to the solving problem,
- velocity of learning process, especially important when the network operates on big multidimensional database.

In the Fahlman's network each input unit is connected to all nonlinear output units, and as well, to all the hidden units, successively added. Outputs of the hidden units by the weights – appropriate connections, also supply output units. In the beginning of the network training there are only input and output units, and its number depends on the specificity of the solved problem. Weight connections has been trained till the minimum of error function was reached. When this occurs, and the training result is not satisfactory, algorithm adds a new hidden unit. The unit is connected to all the inputs, and other hidden units, added earlier. Before the hidden unit is switched on to the network structure, its weights are specially trained, next frozen, and in following learning process they are not changed. Simultaneously, weight connections of hidden unit joined to the outputs are continuously modified in time of training. In such a way every hidden unit represents „one neuron hidden layer." FNN's learning was a supervised process. The weights were adjusted by a original algorithm Quickprop [6] using modified method of Newton in order to obtain a desired input-output relationship. The network finishes to learn when the mean square error on the training data set decreases to the value below 0,006. After a long time of using FNN in similar medical applications we assumed that optimal structure of FNN could be the best for this problem.

We must say that enlarged database used in the experiment (set of 1500 transformed mammograms) has been described correctly by the medicine doctors.

The network we have used had three output nodes, as on Fig.3. We assigned the outputs of these nodes to H-healthy, BT- benign tumor and MT-malignant tumor. When the node's value was one that corresponds to assigned case.

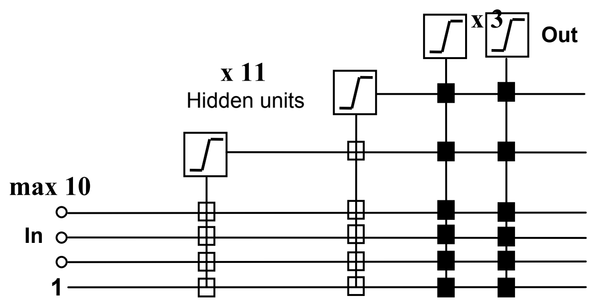

Fig. 3. Fahlman's network realised in CASCOR program.

RESULTS

In the preliminary research ASR method gave us more then 95% correct results of simple "healthy-non healthy" diagnosis (checked on the set of 600 transformed mammograms). In final CDS we decided to distinguish images more precisely. Table 1 illustrates correctness of recognition of healthy nipples, benign and malignant pathologies obtained with the ASR method as a function of threshold of the ill tissue. As it was mentioned before, the best results we have got for 160 and 165 threshold value.

Table1: Results for the ASW method

CORRECTNESS [%]		healthy tissue	benign pathologies	malignant pathologies
Threshold	140	70,20	79,65	86,47
	145	75,42	78,42	87,70
	150	77,72	80,49	88,60
	155	85,61	80,78	88,41
	160	**90,50**	**85,70**	**90,26**
	165	**90,56**	**85,46**	**90,85**
	170	**90,47**	84,20	89,35
	175	89,59	84,71	85,59
	180	89,39	82,57	84,52

As it is shown in Table 1 the correctness of mammogram interpretation improves when the value of threshold equals 165. For this value we obtained about 90% of correctly interpreted mammograms. It should be stated that this result is very good, even much better than proper medium results for oncologist. For the higher values of the threshold, correctness of the healthy tissue detection is nearly constant, but detection of pathologies a little decreases. It seems that for the threshold 170 a lot of information is omitted, and ill tissue can be detected as healthy. The situation is illustrated on fig. 3., where we can also see that the shape of analysed pathology depends strongly on the threshold, so that may be the reason of lower correctness factor for benign or malignant tissue.

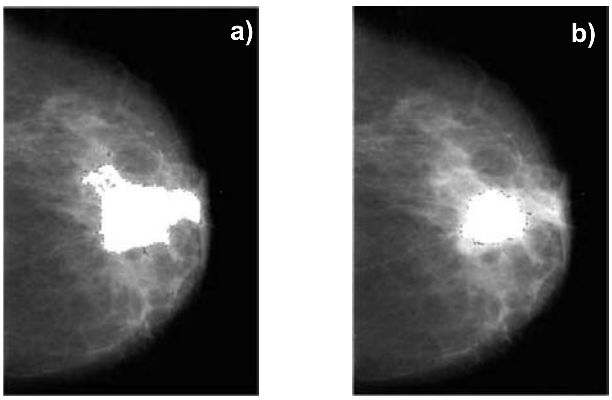

Fig. 3. The mammogram with white part of malignant cancer for two levels of binarization a) 160, and b) 180

As it was mentioned above the database for research with the ROI method was much numerous. We have used 1500 vectors of features calculated from ROI of different center position (the number of the source set of mammograms was the same – 600) and do the cross-validation. Results of the research of ROI method are completed in Table 2 where we present the estimation of the optimal size of ROI radius.

Table 2: Results of the estimation of the ROI radius.

CORRECTNESS [%]		healthy tissue	benign pathologies	malignant pathologies
radius, px	20	90,41	80,31	86,24
	40	**91,42**	**85,86**	**87,75**
	60	89,20	82,52	85,40

Obtained results have shown that the change of the ROI shape from a big size rectangular to circle with different radius is possible and it doesn't decrease the correctness of interpretation. Apparently the best circle-shaped ROI had radius of 40 pixels, but the differences of pathological tissue detection correctness are not such significant as in previous case of ASR method, when we have changed the threshold.. Of course in this case the size and kind of the pathology also influences on the results of diagnosis. For healthy tissue diversity is not very high, similarly for malignant, but is more visibly for benign pathologies.

After that we again have taken 600 images to learn and evaluate the FNN system. We have used the best from estimated thresholds for ASR method, and the best size for the ROI method. The centre of ROI we have selected arbitrarily for each image and the system has generated four ROI quarters around as on shown Fig.1. Then we have calculated ten features for training and testing of the network. Our system classified the images into three categories: H, BT and MT. In the test we have tried to evaluate the significance of the input parameters: that is, we changed the number and the choice of the parameters. Results in Table 3, 4, 5, 6 show the performance of the Fahlman Neural Network classifier for several feature parameter sets. Above the tables are shown the used parameter sets.

Table 3. Accuracy of the system.
Features: NLM, LM, NLM, V, CV

CORRECTNESS [%]		healthy tissue	benign pathologies	malignant pathologies
radius, px	40	79,54	71,4	74,4

Table 4. Accuracy of the system.
Features: V, CV,AFP, LFP, LM, NLM

CORRECTNESS [%]		healthy tissue	benign pathologies	malignant pathologies
radius, px	40	80,1	75,2	84,2

Table 5. Accuracy of the system.
Features: V, CV,AFP, LFP, LM, NLM, CON, VM

CORRECTNESS [%]	healthy tissue	benign pathologies	malignant pathologies
radius, px 40	93,2	89,6	92,1

Table 6. Accuracy of the system.
Features: V, CV, AFP, LFP, LM, NLM, CON, VM, NS, NUS

CORRECTNESS [%]	healthy tissue	benign pathologies	malignant pathologies
radius, px 40	88,4	82,2	85,1

The results show that if we use only some from the selected features such as number of minimum, max level of the grey scale level, V, CV, or AFP diagnostic accuracies are very poor. When we increased the number of the parameters the correctness of diagnosis is significantly better. If we use full future parameter set (V, CV, AFP, LFP, CON, VM, NLM, LM, NS, NUS) the accuracies decrease. The best results of correctness recognition we have obtained for the vector of the features consisted on: (V, CV, AFP, LFP, CON, VM, NLM, LM).

3. CONCLUSIONS

The research let us estimate the best ill tissue threshold for ASR method as 165 grey scale level which guarantee correctness of mammogram interpretation about 90%. This is quite good result, especially that our database (the part from Marsden Hospital) is built on mostly difficult for interpretation cases.

The research on ROI method gave also good results. It could be caused by fact that the circle fits geometrically better than the rectangular for the above application. For the radius of the ROI region of 40 pixels our system correctly interprets 90% of healthy patient mammograms, 86% with benign and 88% with malignant pathology. Its important that the result has been obtained on the database consisted of 1500 images.

In the research we have tried to create the best vector of features computed by the two methods of digital transformation. Numerous training and test of neural networks with different sets of features allowed us to obtain the best set.

For this we have got results on the level: 93% correct interpreted mammograms for healthy tissue (H), 92% for malignant tumor case (MT) and 89% for benign tumor case (BT).

In future we plan to prepare two independent diagnostic systems operating according ASR and ROI methods. First will be full automatic, second will give the opportunity of positioning the centre of ROI region for medicine consultant.

Of course we still can compute features by the two methods ASR and ROI, make common vector of features and introduce to the FNN decision system.

At the moment we are going to start the clinical experiments in the Banacha Hospital in Warsaw.

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