A COMPUTER AIDED DETECTION SYSTEM FOR MICROCALCIFICATIONS IN BREAST PHANTOM IMAGES

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Abstract: Breast cancer control represents one of the greatest challenges that public health service faces nowadays. In order to decrease the death rate from cancer in women, the AGEVISA-PB implemented a Mammography Quality Control Programme to improve the performance of mammographic equipment in Paraiba - Brazil. The evaluation method of these devices is accomplished through breast phantoms that simulate structures found on a mammogram in order to assure the quality of radiographic images. Even so, evaluation by technicians still suffers limitations caused by the visual inspections by individuals, such as long-time benchmarking and subjectivity. The main purpose of this research is to develop a computerised system that analyses radiological images of phantom MAMA-CDM and correlates with human visual perception. The results indicate that the system developed can be used as a second opinion, thus becoming a tool of great utility in aiding medical diagnosis.

1 INTRODUCTION

Breast cancer is a malignant tumour composed of the abnormal development of breast cells. This kind of cancer is most common both in Brazilian and indeed women worldwide, representing 22% of the new cancer cases per year (INCA, 2010). When the disease is diagnosed early in the formation of the tumour, it can be treated more effectively, increasing the chances of cure. The most efficacious method for early detection of this pathology is the mammogram, and it consists of a radiological examination to detect breast lesions, including non palpable lesions (Roveda Junior, 2007).

The mammogram image quality is a constant concern for organisations and experts who face the challenge of early breast cancer detection, in order to save lives and reduce the aggressiveness of treatment (Medeiros and Elias, 2007). This is directly related to the performance of mammographic equipment. The handling and maintenance of mammographic equipment interfere in the medical evaluation quality and, when it is performed incorrectly, it can produce radiographic films that induce misdiagnosis.

Another factor that influences breast cancer diagnosis is the subjectivity of human interpretation of mammographic images. This subjectivity may result in variations in the expert analysis, producing different reports, according to differences of visual perception. Issues such as eyestrain, ambient light, low image quality and radiologist inexperience, may influence the final diagnosis (Byng et al, 1997).

To ensure the quality of mammograms in Brazil, the Brazilian Institute of Cancer (INCA), associated with the Brazilian Radiology Association (CBR) and Brazilian Agency of Sanitary Surveillance (ANVISA), has plans for the foundation of a Quality Programme in Mammograms that will be proposed to the Ministry of Health for countrywide deployment. The programme methodology requires, among other points, the monthly evaluation of a breast phantom imaged in the mammography services (INCA, 2011).

A local Sanitary Surveillance Agency in the Northeast region of the country (AGEVISA-PB) maintains a quality control programme in mammography, which is nationally known because of its scientific technical and social impact. The organisations that perform mammographic

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examinations in the State of Paraiba send monthly a phantom image to AGEVISA-PB, for the quality evaluation of mammography services (Carvalho et al, 2006). The procedure is arduous and time consuming, with each phantom image carefully analysed by experts for approximately 40 minutes. These technicians classify each structure of interest in the phantom by visibility criterion, producing reports for quality image evaluations of the mammographic equipment.

Computer Aided Detection (CAD) is used to reduce the difficulties found in the identification of structures in mammographic images by individuals, providing a second opinion about the expert report. These systems, when specific for mammographic images, promote the integration between medicine and technology to improve the detection in the structures of interest (Porto, 2010).

Nevertheless, even using robust computerised systems, detection of some structures of interest in phantom images is still a difficult task. Because of the smaller sizes in relation to other structures, high contrast details can be confused as artefacts from the revelation process of the radiographic film (Soares and Lopes, 2001).

Artefacts in radiographic film can be related to the processor rolls, the mammographic equipment and the chemicals used for cleaning the equipment or the film revelation. Mammographic images can contain noises such as roller marks, spots, fingerprints, silver deposits, etc.

In the adjustment activity of a radiographic film some fixative solutions are used to dissolve the silver deposits not removed by the reveller solution in the previous step. These deposits are very soluble in water and if not dissolved, can be sensitised by the light, generating similar artefacts to the high contrast detail on radiographic film.

This research aimed to develop a system that automates most of the steps in the procedure of quality control in mammographic equipment currently adopted by AGEVISA-PB. This system intends to detect and classify structures who simulate microcalcifications of interest in breast phantoms by visibility criterion, correlating with the human visual system, in order to reduce the subjectivity in image inspections in the phantom MAMA-CDM (CBR, 2011).

2 MATERIALS AND METHODS

This system was developed using the Java programming language along with the *ImageJ*, open source software focused on the development of image processing and analysis applications. The algorithms developed were incorporated into *ImageJ* through the use of plugins, and the system interface was integrated with the system functionalities.

The system uses the *Microtek* scanner *ScanMaker i800* model to digitize the phantom images in grayscale, 16 bits of contrast resolution and 1200 x 1200 dpi of spatial resolution.

One of the approaches for visual inspection on radiographic film is to determine the visibility of structures of interest in the phantom MAMA-CDM images. To detect these structures it is necessary that the system defines different regions of search for each phantom, due to the structure of interest location which varies from one phantom to another because of their handmade production.

2.1 Phantom MAMA-CDM

Breast phantoms are used to assess the quality control of mammography services. The main purpose of these phantoms is in the evaluation of mammographic equipment, through the images that contains structures which simulate the breast tissues.

The AGEVISA-PB developed a Programme of Quality Control in Mammography, which uses the phantom MAMA-CDM for the production of radiological images from mammography equipment in the State of Paraiba - Brazil. The use of this breast phantom is recognised by the CBR (CBR, 2001). It is interesting to know that these phantoms are produced in a handmade mode, simulating a compressed breast between 4 cm and 5 cm, with test structures similar to the anatomical structures present in the breast and a range of optical densities.

Figure 1 presents the breast phantom MAMA-CDM, its radiographic image and the representation of its structures. It is estimated on these images (A) the background optical density, (B) the details of low contrast (fibrous tissue), (C) the low contrast thresholds (discs), (D) the high contrast details (microcalcifications), (E) the structures who simulate tumour masses and (F) the spatial resolution (metal grids).

2.2 High Contrast Details

The images used have high resolution, which eventually results in poor computer performance. Therefore, areas of search were delimited for the structure location in images of phantoms. From the moment it receives an input image, the system automatically adjusts its orientation through a

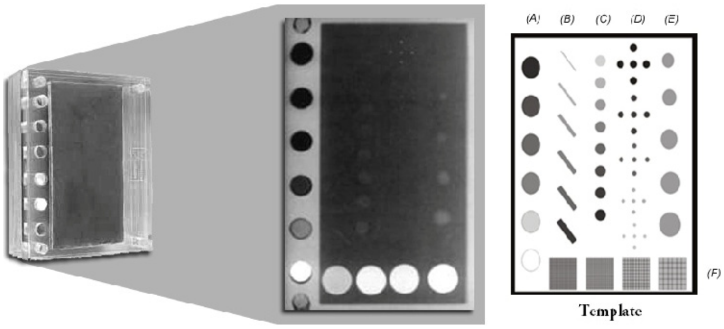

Figure 1: Breast phantom MAMA-CDM, its radiological image and the representation of its structures.

rotation based on the angle between the brightest optical density and the darkest optical density. After the adjusted image, is executed it looks for other structures in the search regions by the correlation matching method (Gonzales and Woods, 2002).

The visibility determination of each structure of interest is assessed by a data mining tool called WEKA, with the use of the J48 classifier. This classifier will generate a model, where it is necessary preselect some image attributes to execute the training stage of the system (Martinez and Sanjurjo, 2009).

In the production of each learning model, the J48 algorithm was used because of its simplicity and satisfactory results. Moreover, in previous researches, other algorithms have been tested to develop the learning model, but the best results were achieved by the J48 algorithm (Barufaldi et al, 2011).

The attributes such as average of pixel images, variance, standard deviation, mode, average of structure pixels, average of background pixels, difference of structure and background averages, and Weber Ratio were preselected for the production of learning model. It is noteworthy that not all attributes used in the training stage will be employed for the classification of structures, since some of the image characteristics are not considered relevant by the algorithms, and they are automatically discarded by WEKA tool. In order to define which attributes will be used, an automatic selector (*AtributteSelection*) was used, which is implemented by the WEKA tool.

Table 1 represents the attributes extracted from each structure also used in the training stage, where $p_e(i,j)$ and $p_b(i,j)$ are the grayscale of pixels in the inner region (structure) and outer (background) of the filter with size $w*h$ at position (i,j) of the image.

The filters used in the correlation operations are composed of two parts, the inner and outer region, illustrated in Figure 2. The inner region tries to match the inside structure, while the outer region tries to match the background.

Table 1: Attributes selected from the image after the detection of the structures of interest.

Attribute	Equation
Average of the structure pixels	$\mu_e = \sum_{i=1}^{w}\sum_{j=1}^{h}\frac{p_e(i,j)}{(w*h)}$ #
Average of the background pixels	$\mu_b = \sum_{i=1}^{w}\sum_{j=1}^{h}\frac{p_b(i,j)}{(w*h)}$ #
Difference of the average grayscale of the structure pixels and background	$\Delta\mu = \mu_e - \mu_b$#
Weber Ratio (GONZALES; WOODS, 2002)	$W = \frac{\Delta\mu}{\mu_e}$ #

A total of 100 clusters of high contrast detail were extracted from these images for training purposes. These structures were classified by experts according to their visibility, i.e., if they are visible or not. It is noteworthy that the image reports were produced by two or more technicians, in order to reduce the subjectivity of visual inspection, increasing the system consistency.

In the training stage a file is created from the default format of the WEKA (.ARFF), with all the input data mentioned above. Then, the J48 algorithm of the WEKA is used to generate the decision tree for each structure of interest. To produce and test the learning models, leave-one-out cross-validation was used.

In the classification stage the decision trees are implemented based on models obtained in the training stage. One hundred images were used for classification tests, with 500 clusters of high contrast details analysed. It is important to note that the images produced in the classification step are distinct from those of training.

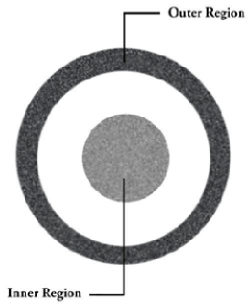

Figure 2: Example of the filter used for the detection and the classification of a high contrast detail of the phantom image.

From the classification of these structures and the comparison between the expert reports and the reports produced by software, it is possible to determine statistical measures such as accuracy and efficiency.

The software behaviour is evaluated using ROC curves for each structure of interest, where the sensitivity and specificity of the system are verified (Zweig and Campbell, 1993). According to the attribute automatic selector of the WEKA, $\Delta\mu$ is the attribute that was always present in all models. Because of this, in the development of the ROC curves the attribute values of $\Delta\mu$ were varied ranges [20,000; 50,000], since this was the most important attribute in the training stage in all structures of interest.

3 RESULTS

The classification results using the J48 algorithm produced the misclassification tables for each kind of structure of interest, indicating the accuracy rates of the classification. These measures are presented in Table 2.

Table 2: Misclassification table of the high contrast details.

		J48 Classification	
		Visible	Not Visible
Expert Classification	Visible	0.99	0.01
	Not Visible	0.00	1.00

Table 3 presents the rates of accuracy, sensitivity, specificity, efficiency, positive prediction and negative prediction, and Matthews coefficient to the classification of each structure of interest.

Table 3: Effectiveness measures of the software to the classification of the high contrast details using the J48 algorithm.

Measure	**Value**
Accuracy	0.9906
Sensitivity	0.9882
Specificity	1.0000
Efficiency	0.9941
Positive Prediction	0.9882
Negative Prediction	1.0000

The sensitivity values were very close to the positive predictions. This occurs because of the high number of high contrast details compared to the low rate of predictive errors (false positives and false negatives). The same applies to the specificity and negative prediction values.

Figure 3 allows observing the behaviour of the system to the structures classification by ROC curves.

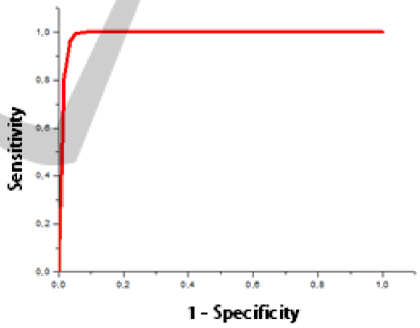

Figure 3: ROC Curves to the classification of the high contrast details (AUC = 0.98).

Figure 4 shows the marking of a high contrast detail group detected correctly even with the presence of the artefacts in a phantom image after the processing by system.

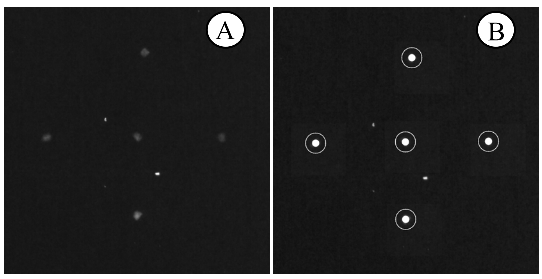

Figure 4: (A) High contrast detail group with the presence of the artefacts, before the processing and (B) the same group detected after the image processing.

4 DISCUSSIONS AND CONCLUSIONS

This research presents a method for localizing and classifying, with high precision, high contrast details clusters in phantom images. The next step of this work consists of executing comparative tests between the techniques presented here with researches related to the theme.

Statistical measures of the software, which were presented in the previous section, suggest that the classification of the structures of interest closes with the expert vision of the AGEVISA-PB.

Despite of the size of the structures which simulate the microcalcifications and the possibility of the confusion with noise, the classification of these groups represented high success rate of the system (99.41%). These results are due to the reduction in size of search regions in the images in each phantom, as well as the highest contrast of these structures. With the well-defined boundaries of the regions, the probability of artefacting the artefacts and classification from the radiographic film instead of structures of interest is reduced.

With the implementation of the system in the AGEVISA-PB, planned for the coming months, it is expected that the experts will learn how to use the software and the reports generated by computer analysis of the phantom images as an aid to the visual inspection. Thus, part of the process for the Quality Control in Mammography will be automated and the subjectivity in the image evaluation may well be reduced.

After usability tests with the experts and improvements in the user interface, the system will be introduced in the establishments which provide mammography services, to execute their own quality control in an efficient mode and with the appropriate frequency.

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