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EVALUATION OF SPATIAL RESOLUTION USING ANALYSIS TEXTURE IN BCR’S BREAST PHANTOM IMAGES

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ABSTRACT

Mammography is the main radiographic technique for imaging the breast, being indicated for cancer diagnosis and clinical monitoring. In Brazil, the National Quality Program in Mammography (NQPM) was developed. This program provides radiation exposure reference levels and evaluates the image system quality through a visual inspection of images obtained with the breast phantom. Texture is an important characteristic that can be used to identify or describe an image. It refers to the spatial arrangement of pixel’s gray levels in a given region. Texture analysis technique can be used to obtain spatial resolution results from phantom’s grids present in the images. Therefore, the aim of this work is to develop texture analysis algorithms to perform an automatic quality evaluation of Brazilian College of Radiology (BCR) breast phantom images. For this study, BCR phantom images were collected from different facilities in Belo Horizonte, Brazil. The methodology consists in selecting a region of interest (ROI) and then performing image background subtraction and filtration. Thereafter, statistical values are calculated to quantify the gray level spatial distribution. Statistical parameters were used to quantify the differences between periodic models. These algorithms were developed in MATLAB and the test objects evaluations were made following the NQPM parameters. The visual and computerized evaluations were compared. The results showed that the developed algorithms can differentiate the four different grids of BCR phantom images. The use of these digital image processing techniques in the test object images allows an objective evaluation. Therefore, the developed algorithms help to improve the evaluation performed by quality assurance programme specialists.

Keywords: Mammography, Digital Image Processing, Texture Analysis.

1. INTRODUCTION

Breast cancer is the most common cancer and the second cause of cancer death among women [1]. Mammography is considered the most sensitive exam to early detection of breast cancers. However, the interpretation of lesions in mammographic images is complex and depends on the radiologist's experience for an accurate diagnosis [2]. In Brazil, the National Program for Quality in Mammography (PNQM), which began as a pilot project developed by the National Cancer Institute (INCA) in partnership with the Brazilian Health Surveillance Agency (ANVISA) and the Brazilian College of Radiology (BCR), promotes actions to control the quality of mammography [3]. As result from the pilot project, and in order to ensure that the mammographic diagnosis is done properly and efficiently, the Health Surveillance of Minas Gerais (VISA-MG) created the "Monthly Monitoring Program Mammography Quality". One goal of the program is to assess the quality of examinations through a visual inspection of the image of the breast phantom.

Breast phantom simulates a breast compressed with thickness between four and five centimeters. The BCR phantom was designed to test the performance of a mammography system by a quantitative evaluation of the system's ability to image small structures similar to those found clinically like microcalcifications, fibers and tumor masses. One of the parameters that determine the quality of image is the spatial resolution. The BCR phantom has 4 metal grids to evaluate it, corresponding to 12, 8, 6 and 4 lp/mm (line pairs per millimeter). The image will be considered appropriate if the spatial resolution is equal or greater than 12 lp/mm, thus the four metal grids should be viewed considering a conventional mammography image (film). For digital systems, the spatial resolution ranges from five to ten line pairs per millimeter, but they have better contrast resolution [4].

In the last decades, several studies using image processing techniques have been developed as part of Computer-aided Diagnosis (CAD) schemes, which became one of the major research topics in medical imaging and diagnostic radiology. Many different CAD schemes are being developed for use in the detection and/or characterization of multiple lesions found in various types of medical images [5, 6]. In this study, we developed algorithms to evaluation perform of these grids on images obtained from BCR phantom using automated digital image process techniques, such as, texture analysis.

Once the grids have different textures, it is feasible to use a texture recognition algorithm to identify them. The concept of texture in a digital image is attributed to the distribution of gray level values between pixels in a region of interest (ROI) in the image. The textures contain information about the spatial distribution and the brightness variation; this describes the structural arrangement of surfaces and the relations between neighboring regions. Therefore, the use of textural information is presented as a suitable approach for describing regions of the image. A texture analysis, using some or all of the texture features 14 proposed by Haralicket al. [7], is based on the Gray Level Co-Occurrence Matrix (GLCM), which is a popular approach to analysis and classification of medical images. In the mammography case, these texture features can provide information about the different types of tissues present in the breast and eventual abnormalities [8].

In recent years, many analyses of image's reference phantoms, applying different digital processing techniques were performed to quantitatively evaluate the quality of the image produced by mammography equipment. Among the most used, we can mention the American College of Radiology (ACR) phantom [9, 10], the phantom manufactured by CIRS (Computerized Imaging Reference Systems) company [11], the accredited breast phantom in France (MTM 100/R) [12], the “Rachel” Anthropomorphic Breast phantom Gammex 169 [13] and software breast phantom [14].

In this study we were developed algorithms for the evaluation of spatial resolution using BCR phantom images, performing a texture analysis of the four metal grids. The image resolution is evaluated considering the number of visualized grids.

2. MATERIALS AND METHODS

2.1 Description, acquisition and digitization of images.

The phantom used in this study was developed by the Brazilian College of Radiology. It consists of three plexiglass plates of 10 mm 120 mm 160 mm and one plexiglas plate of 20 mm 120 mm 160 mm which contains a 5 mm 70 mm 140 mm wax insert and a step wedge that produces five optical densities used to assess image contrast. In the wax insert are embedded the following structures: four metal grids of 4, 6, 8 and 12 lp/mm (G1 to G4) to evaluate spatial resolution; five groups of Al_2O_3 specks of 0.45, 0.35, 0.30, 0.25 and 0.18 mm (m1 to m5), grain sizes to simulate microcalcifications; eight polyester discs of 6 mm diameter and thickness ranging from 0.1 to 0.8 mm (D1 to D8) to simulate low contrast areas; six nylon fibers of 1 cm length and 1.4, 1.2, 0.8, 0.7, 0.6 and 0.4 mm (F1 to F6) diameters to simulate fibrils; and five nylon spherical caps of 2.00, 1.5, 1.0, 0.75 and 0.50 mm (M1 to M5) heights to simulate tumor-like masses [15]. In the phantom are also present low contrast structures Figure 1 shows a schematic diagram of the BCR phantom.

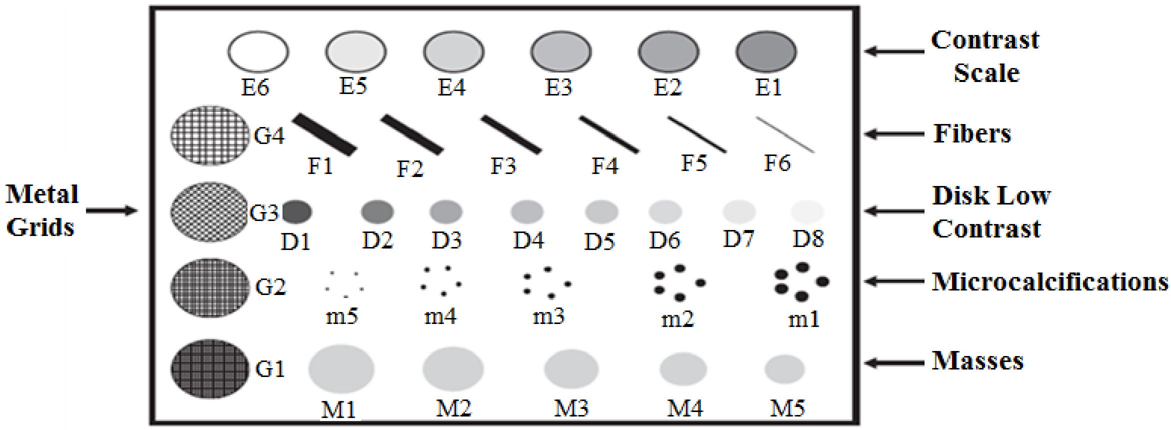

Figure 1. Schematic diagram of BCR phantom

In each category of test objects, the size and/or contrast of objects gradually decreases. For example, microcalcifications group (m1) are larger grains while m5 group are smallest, thus a similar convention for other structures. In the case of the grids, G1 represents a lower number of line pairs per millimeter (~4lp/mm) while G4 is the largest amount (~12 lp/mm).

The evaluated films were taken from the VISA-MG database. Images were acquired in different mammography facilities and were sent as part of the Monthly Monitoring Program. For this study 10 images were selected, and they were evaluated visually for three trained observers. The appraisers identified the number of test objects visible in BCR phantom images. Images were placed one at a time in a light box (luminance ~ 3000 cd/m2) and they were read by using a magnifier glass. In the Radiation Protection Laboratory applied to Mammography (LARAM/CDTN/CNEN), the images were digitized using the ScanMarker 9800XL from Microtek, with a resolution of 1200 dpi, RGB color pattern and saved in TIFF (Tagged Image File Format) format, which presents no loss of information.

The evaluation of the spatial resolution is carried out with a texture analysis of these grids on the phantom images. For this, ROIs of 250 x 250 pixels are selected within each of the grids, as shown in Figure 2.

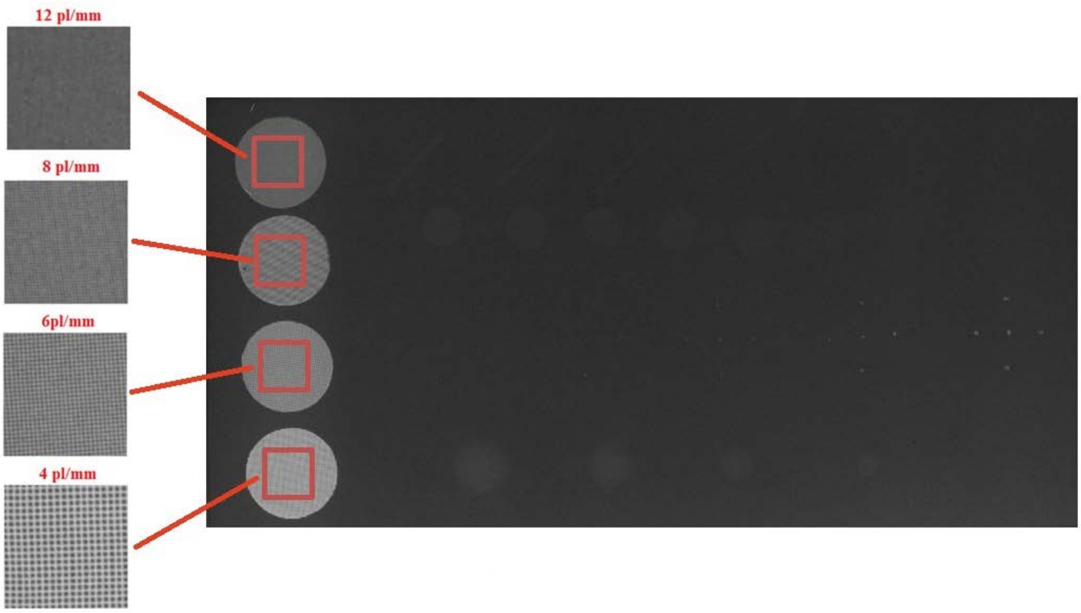

Figure 2. Selection of ROIs of 250 x 250 pixels.

2.2 Texture Analysis

Texture analysis is a technique for evaluating the position and intensity characteristics of the pixels and the gray level intensity of the digital images. Texture features are mathematical parameters calculated from the distribution of pixels.

According to the methods used to evaluate the interrelationships of pixels, the three main approaches used in image classification for describing textures are statistical, structural and spectral [16], as are described below:

• Statistical approaches: the texture is defined by a set of standard local measures taken. Measures include common statistical entropy, correlation, contrast and variance;
• Structural approaches use the idea that the textures are composed of primitives arranged approximately regular, repeating manner, according to well-defined rules. As an example, one can cite the description of the texture based at regularly spaced parallel lines;
• Spectral approaches are based on Fourier spectrum properties, being used primarily in the global frequency by identifying peaks in the high energy spectrum for detection an image.

In this work, texture analysis was performed from statistical approaches obtained from extracted attributes of the gray levels co-occurrence matrix. GLCM is a statistical method that provides spatial relationships between the image gray levels, allowing the extraction of attributes representing characteristics of texture as roughness, granularity, roughness and regularity [17]. The objective was to find a probabilistic decision rule associating the texture of the grids and thus define if the visibility is possible.

2.3 Gray Level Co-Occurrence Matrix (GLCM).

GLCM is a two-dimensional matrix, generated by counting the occurrences of combinations of gray pixel shades and its neighboring pixel. For each of the possible combinations between one pixel and its neighboring pixel, it creates an element in the gray scale co-occurrence matrix, so that the size of the GLCM is t x t, where t is the number of gray levels present in the original image [14]. One element matrix in position (i, j) indicates how times original image a pair of gray levels of points (i, j) is given and separated by distance (δ) and defined in the direction (θ) chosen.

Illustrating the method, Figure 3 shows the process for obtaining the gray scale co-occurrence matrix. An image of 4x4 size, t = 4 gray levels, the co-occurrence matrices are of size 4x4. Considering this example when $\theta = 0$ ° and $\delta = 1$, thus to position (0, 1) equivalent how many times appear the gray level of the relationship with the 0 gray level 1 at a distance 1 to 0 degree. Figure 3 shows that this relationship occurs twice in the image [15].

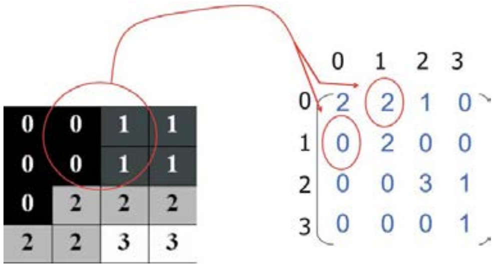

Figure 3.Gray Level Matrix and GLCM.

Textural features extracted from GLCM based on the characteristics of Haralick [7], can be described in up to 14 different descriptors as: energy (uniformity), contrast, correlation, inverse difference moment, mean sum, mean difference, entropy, entropy of the sum, difference entropy, variance of the sum of the difference variance and correlation information measure . This study used five of these descriptors, which are shown in Table 1 with its characteristics and the type of information obtained from each of them.

Table 1. Characteristics of the texture attribute.

Statistical	Description and information obtained
Contrast	Measures the local variations in the GLCM. Returns a measure of the contrast between the intensities of one pixel and its neighboring pixel. For a constant image (same tones of gray to the full extent), the contrast is 0 (zero).
Correlation	Measure the joint probability of occurrence of the specified pixel pairs. Range of possible values: -1 to 1
Energy	Also known as uniformity or the second angular momentum. Returns the sum of squared high elements within GLCM. Range of possible values: 0 to 1 The energy has value 1 for a constant image (same gray tones in all image).
Homogeneity	Returns a value that represents the proximity of the distribution of elements in relation to the diagonal of the GLCM. Range of possible values: 0 to 1.
Entropy	Provides the degree of dispersion of gray levels in image, measuring the information contained in pixel. Many pixels with the same gray level value mean an image with little information or small entropy.

In this study were used the MATLAB® program to create the GLCM of breast phantom images using the *graycomatrix* function. The *graycomatrix* function creates the co-occurrence matrix calculating how many times a pixel with intensity (gray level) *i* occurs in a specific spatial relationship to a pixel *j*. The spatial relationship was defined as the pixel of interest and the pixel to its immediate right (horizontally opposite). The number gray levels of image determines the size of GLCM, by default the *graycomatrix* function uses the scale to reduce the number of intensity values of an image to eight gray levels. However, this parameter is changeable. GLCM is used to obtain features of the gray levels spatial distribution in the image.

3. RESULTS

For the attributes of the statistical method used, probabilistic decision rules were established to define whether the grids are visible. In Table 2 the evaluation criteria are defined.

Table 2. Evaluation criteria of grids.

Statistics	Acceptance
Contrast	Value greater than 0.1. Value minor means a constant image without the variation due to the pairs of lines present in the ROI.
Correlation	Values between -1 and 1. The correlation graph should generate a recurring image that ensures a link between gray tones.
Energy	Value less than 0.5
Homogeneity	Value less than 0.9

The contrast and energy are the main attributes used to define the visibility of grids in the image. Contrast is an estimate of the mean square of the variation of gray levels between pairs of image elements. Energy is a uniformity indicator or smooth textures. The correlation graphs vs. horizontal displacement in the ROI can confirm a lack of correlation between the pixel and its neighbors.

The algorithms were applied to the ROIs on standard image (test image). In the Table 3 shows values obtained for each of the attributes used.

Table 3. Results of texture attributes on ROIs in a standard image

Region	Contrast	Correlation	Energy	Homogeneity	Entropy
G1	2.1374	0.0083	0.0750	0.5752	6.6761
G2	1.1429	0.00034	0.1492	0.6638	5.7860
G3	0.9282	0.0036	0.1916	0.7008	4.8563
G4	0.4708	0.0397	0.3255	0.7646	3.9622

Figure 4 shows the correlation graphs vs. horizontal components of the ROIs for each of the four grids. In the graphs horizontal component, there is a strong periodic component in the image, which suggests that it is possible to visualize the metal grids. The correlation was used to measure the similarity between two sequences.

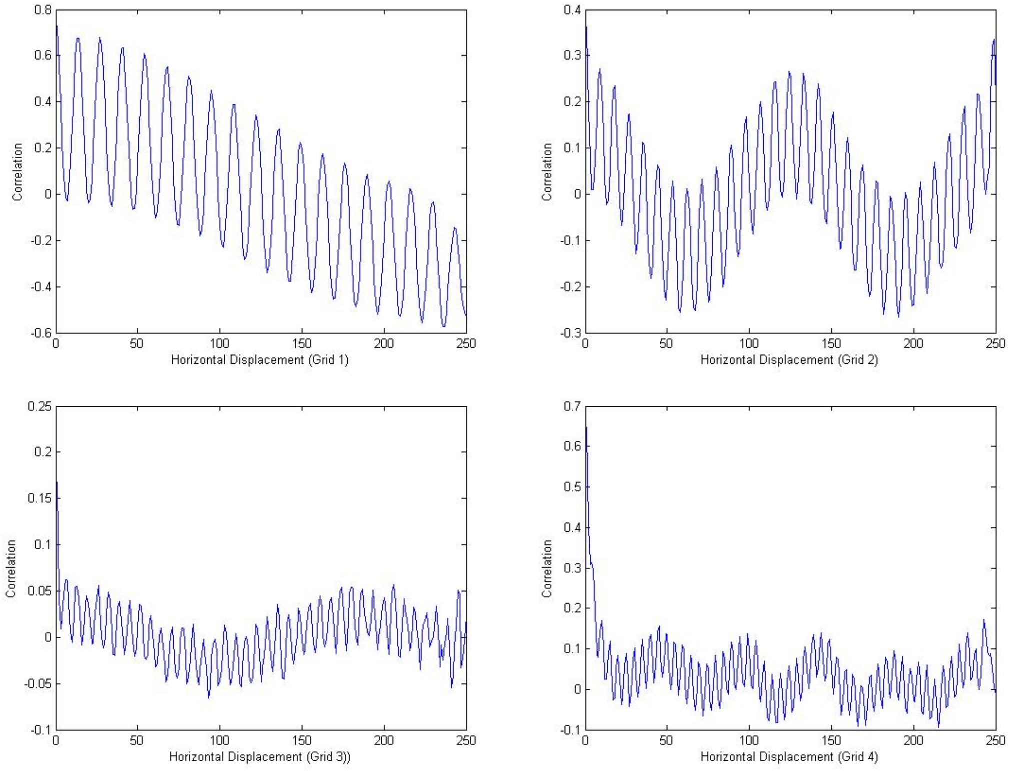

Figure 4. Texture Correlation vs. Horizontal displacement in the four ROIs on test image.

Ten different images were taken of the VISA-MG database were evaluated. The films were visually evaluated by three trained appraisers (Figure 5). Then the films were scanned and the algorithms were applied them.

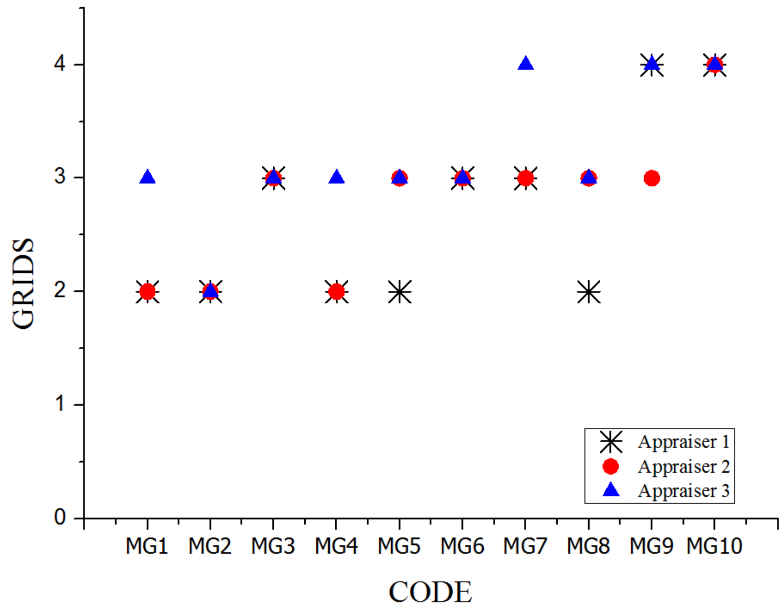

Figure 5. Visual analysis of grids.

The discrepancies between the appraisers involved are attributed to their visual perception differences potentially, due to contrast and spatial resolution specifically.

An example, Table 4 show the attribute values obtained for the four grids of two different images. The first four grids are visible (Image 1) and in the other G4 grid is not distinguishable (Image 2). The technique was applied in the same way in 10 images.

Table 4. Comparison of features texture of two images.

	G1		G2		G3		G4	
	Image 1	Image 2	Image 1	Image 2	Image 1	Image 2	Image 1	Image 2
Contrast	1.3760	2.0445	1.4411	1.1165	0.9109	0.9146	0.0047	0.3123
Correlation	0.2297	-0.0033	0.0033	0.0061	0.00089	0.0021	NaN	0.0126
Energy	0.0954	0.0806	0.1095	0.1459	0.1899	0.1847	0.9907	0.4766
Homogeneity	0.6368	0.5814	0.6278	0.6668	0.7009	0.6981	0.9977	0.8438
Entropy	6.4295	6.6533	6.2245	5.7648	4.8128	4.8417	3.7883	4.0701

Using the previously defined criteria and the values obtained for the fourth grid ROI, G4 (Image 1), can be said that the grid is not visible, a contrast lower than 0.1 (0.0047), an energy value greater than 0.5 (.9907) and a homogeneity greater than 0.9 (0.9977). Moreover, the correlation value is not defined by the algorithm. This result can be seen in Figure 6, which shows the selected ROIs in the two images with their respective correlation graphs, showing the grid G4 of image 1 has a correlation graph without regular periodic relationship.

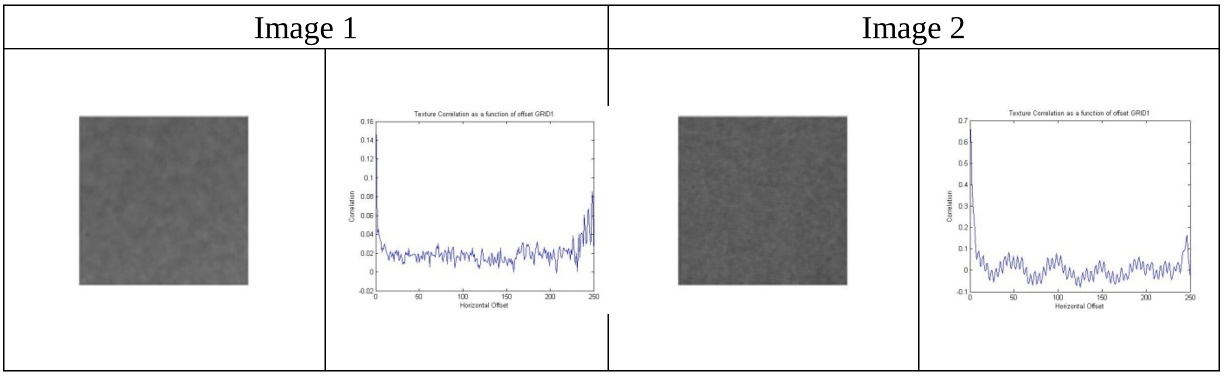

Figure 6. Comparison of the correlation graphs of ROI-G4 in two images.

The comparison of the mean visual evaluation by three appraisers with its standard deviation, and the evaluation obtained by the algorithms is shown in Figure 7. The algorithm analysis identified the number of grids approximate visual appraisers. The results show that computational method introduced is suitable for identifying images with similar level of quality for medical diagnosis using a quality control test image.

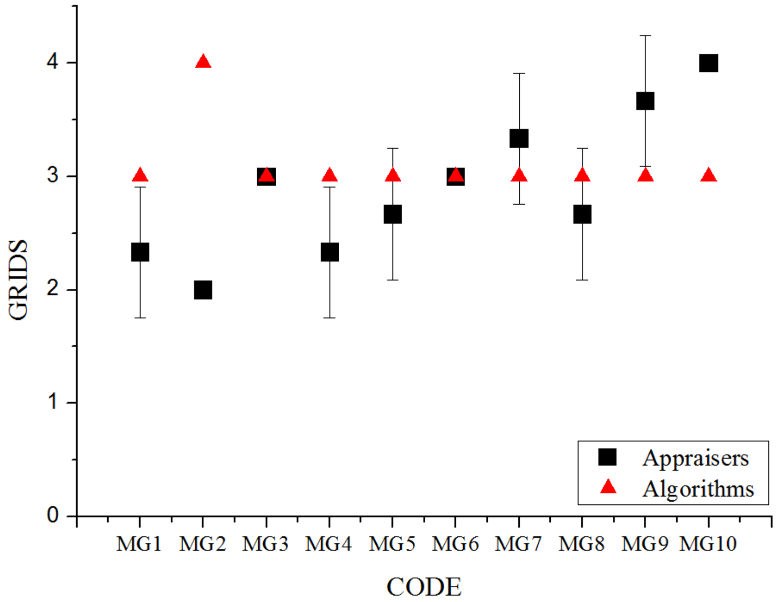

Figure 7. Comparison of visual and automatic evaluation grids in BCR phantom images.

4. CONCLUSIONS

This paper described the texture analysis technique to evaluate the spatial resolution in X-ray images of the breast BCR simulator. Texture features are a mathematical representation of image characteristics. This analysis can be applied to any image regions to be distinguished from such descriptions. The texture was described in terms of statistical measures indicating the spatial distribution of intensity variations in the image. GLCM were used to estimate the statistical measures whose calculations are computationally simple and fast.

The extraction of texture features and the analysis of these attributes in ROIs were statistically appropriate. The use of the developed algorithms represents a reduction of time and subjectivity in the evaluation of the BCR breast phantom images.

From the research carried out, new proposals for future work arise as the use of spectral approaches by applying the Fourier transform, or by using the texture features to evaluate mammography images of patients.

5. ACKNOWLEDGEMENT

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