IMPROVED SPATIAL GRAY LEVEL DEPENDENCE MATRICES FOR TEXTURE ANALYSIS

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ABSTRACT

In this paper, we will focus on the Spatial Gray Level Dependence Matrices SGLDM to extract the Haralick's texture features of the ultrasound breast lesions. This method relies on the manual selection of the region of interest, which results in the dependence of parameters values on the extracted region. For that reason, an improved Spatial Gray Level Dependence Matrices based on the segmented masses using active contour was applied. This method outperforms the existing SGLDM method because it allows establishing a well determined threshold for the classification of lesions.

KEYWORDS

Texture Analysis, Co-occurrence Matrix, Spatial Gray Level Dependence Matrices, Breast Ultrasound

1. INTRODUCTION

Texture analysis is an essential issue in image processing. It comprises a set of mathematical techniques used to quantify the different gray levels within an image in terms of intensity and distribution.

Texture represents the spatial arrangement of pixels' gray levels in a region. So, it can be divided into two classes: periodic texture and random texture. Consequently, we can distinguish the structural approaches and the statistic approaches to calculate a number of mathematical parameters that characterize the texture. Structural approaches are more suited to the study of periodic or regular textures. However, statistic approaches are used to characterize fine and non homogeneous structures without apparent regularity. That is why; this type of method is generally applied in medical imaging.

Numerous methods belonging to statistic approaches have been proposed in the literature. Indeed, we can mention the First Order Methods (FOM) [1], the Spatial Gray Level Dependence Matrices (SGLDM) [2, 3], the Gray Level Difference Methods (GLDM) [4], the Gray Level Run Length Statistics (RUNL) [5], the Fourier Power Spectrum (FPS) [4], the Fractal Dimension Texture Analysis (FDTA) [6], the Surrounding Region Dependence Method (SRDM) [7], and the Histogram Measures (HM) [8].

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Texture can be used in many application areas, such as image segmentation [9], object recognition [10], or classification [11]. Moreover, the texture of image plays an important role in the differentiation of ultrasound breast lesion during the diagnosis because echogenicity and echostructure are essential parameters for the evaluation of lesions. So that, textural variation in the ultrasound image has been found as a useful feature to identify benign and malignant tumors. Nevertheless, according to the subjective observations and individual experiences, radiologists may qualitatively attribute the texture characteristics differently. That is why; texture analysis is needed to describe texture quantitatively. So, the subjective variation will be eliminated and the analysis of image texture can be facilitated.

Chen et al. [12] demonstrate that the application of the feature parameters derived from the co-occurrence matrix to quantify the texture of ultrasound images is useful in the differentiation of various breast lesions. Sivaramakrishnaa et al. [10] investigate the use of Haralick's texture features [2] through SGLDM and posterior acoustic attenuation descriptors for the characterization of ultrasound breast lesions. Bader et al. [13] applied the first order texture, the gray level histogram, the Fourier analysis, and the co-occurrence matrix to evaluate breast tumors.

In this study, we will focus on the SGLDM method to extract the Haralick's texture features of the ultrasound breast lesions. This method relies on the manual selection of the region of interest ROI, which results in the dependence of parameters values on the extracted region.
For that reason, an improved SGLDM method based on the segmented masses using active contour method [14] was applied.

This paper is arranged as follows: In section2, we describe our data base. Next, we present the SGLDM method as well as the textural parameter, and we explain the improved SGLDM method. Section 3 presents the experimental results and the discussion. Finally, Section 4 concludes the paper.

2. MATERIALS AND METHODS

2.1. Data base acquisition

In this study, a total of 50 cases of breast ultrasound lesions were acquired by an ultrasound system Toshiba and a linear array transducer with variable frequency from 5 to 12 MHz. They were all proved by pathologic results to be either benign or malignant soft-tissue tumors. We distinguish 31 benign lesions and 19 malignant lesions. The patients were all female with the ages ranging from 23 to 68 years old.

2.2. Spatial gray level dependence matrices (SGLDM)

SGLDM is a statistical method which consists in constructing co-occurrence matrices to reflect the spatial distribution of gray levels in the region of interest. SGLDM is based on the estimation of the second order conditional probability density $g(i,j,d,\Theta)$. This means that an element at location (i, j) of the SGLD matrix signifies the probability that two different resolution cells which are in a specified orientation Θ from the horizontal and specified distance d from each other, will have gray level values i and j respectively.

The angle is used to evaluate the direction of texture, and the application of several distance values can provide a meaningful description of the size of the periodicity texture. Thus for different Θ and d values, different SGLD matrices result. The angle Θ is usually restricted to

values of 0, 45, 90, and 135°, and the distance *d* is limited to values restricted to integral multiples of pixel size.

Figure 1 shows how calculate SGLD matrix with Θ =0 and *d*=1. Element (2, 1) in the SGLDM contains the value 2 because there are two instances in the image where two horizontally adjacent pixels have the values 2 and 1. Element (4, 1) in the SGLDM contains the value 1 because there is only one instance in the image where two horizontally adjacent pixels have the values 4 and 1.

The size of the SGLD matrix is *Ng* Ng*, where *Ng* is the maximum gray level of the region of interest.

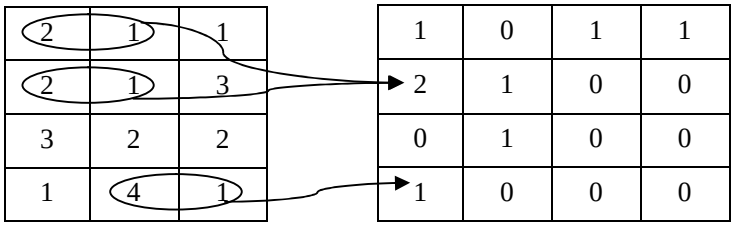


Figure 1. Construction principle of co-occurrence matrix

Different parameter of texture reflects different property in the image. Haralick et al. proposed a large number of features called Haralick's texture features [2] derived from the co-occurrence matrix. We will focus on and discuss contrast, homogeneity, energy, entropy, mean, and variance, in this study. These parameters are briefly described as follows [3, 15]:

- Contrast: It is a measure of the local variations of gray levels present in an image. Images with large neighboring gray level differences are associated with high contrast. This parameter can also characterize the dispersion of the matrix values from its main diagonal. Contrast is defined as follows:

$$cont = \sum_{i} \sum_{j} (i-j)^2 g(i,j) \tag{1}$$

Where $g(i, j)$ corresponds to the elements of co-occurrence matrix, ie the probability of moving from a pixel with gray level *i* to a pixel with gray level *j*.

- Homogeneity: This parameter, called also Inverse Difference Moment, measures the local homogeneity of an image. It assigns larger values to smaller gray level differences within pixel pairs. This parameter has opposite behavior of the contrast. More the texture has homogeneous regions, more the parameter is high. Homogeneity is written as:

$$\text{hom} = \sum_{i,j} \frac{1}{1+(i-j)^2} g(i,j) \tag{2}$$

- Energy: This parameter is a measure of image homogeneity; it reflects pixel-pair repetitions. Homogeneous images have very few dominant gray tone transitions, which result into higher energy. Energy is defined as follows:

$$ener = \sum_{i,j} (g(i,j))^2 \tag{3}$$

- Entropy: The feature entropy is a measure of non-uniformity in the image or region of interest. If the image is heterogeneous, many elements on the co-occurrence matrix have small values,

which imply that entropy is very large. Entropy is inversely correlated to energy, it is given by the following expression:

$$ent = -\sum_i \sum_j g(i, j) \log(g(i, j)) \tag{4}$$

- Mean: The mean is determined by the homogenous brightness or darkness of the image. The more homogeneously bright the image is, the higher is its mean, and vice versa. The mean is written as:

$$mean = \sum_i \sum_j g(i, j) \tag{5}$$

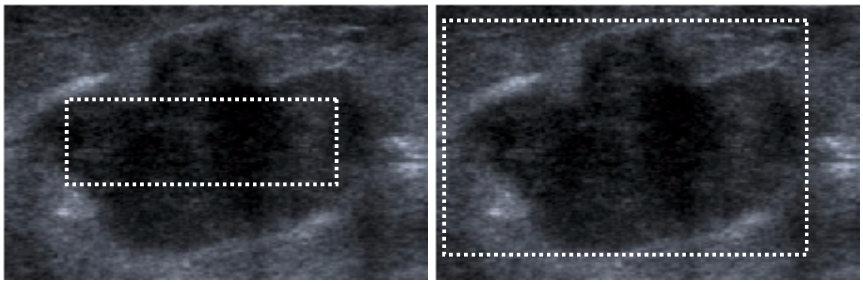
- Variance: It is a measurement of heterogeneity and was correlated strongly with standard deviation. It characterizes the distribution of gray levels around the mean value calculated above. Therefore, variance increased when the gray levels values differed from their means. The expression of the variance is:

$$\text{var} = \sum_i \sum_j (i - mean)^2 g(i, j) \tag{6}$$

2.3. Improved spatial gray level dependence matrices

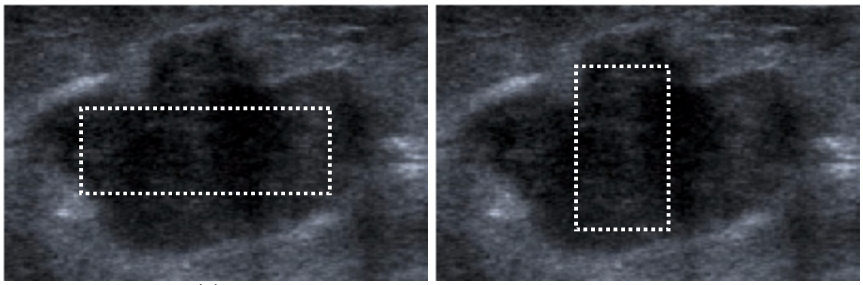
In the literature, authors selected manually a rectangle region of interest inside or outside the solid mass to calculate textural features derived from SGLDM method [10], [12], [13]. In both cases this poses a problem. In fact, if the rectangle is inside the solid mass, it should be as large as possible to include the most of mass. In this case we can lose information that may be useful in calculating the parameters (figure 2a). However, if the rectangle is outside the solid mass, unnecessary information included in the calculation of features (figure 2b).

Furthermore, the selection of the rectangle region of interest is operator dependant. Figure 3 shows two possibilities of selecting this rectangle which leads to different results.



(a) (b)

Figure 2. Two possibilities of selecting region of interest
(a) Selected rectangle inside the ROI, (b) Selected rectangle outside the ROI



(a) (b)

Figure 3. Two possibilities of selecting rectangle inside the region of interest
(a) Possibility 1, (b) Possibility 2

All these disadvantages can affect the precision in computing textural features. So, to achieve more accuracy, texture analysis should be ideally invariant. This paper attempts to fill this gap by presenting an improved SGLDM method based on the whole segmented lesion. The segmentation of breast masses was carried out automatically using active contour method [14].

In fact active contour, originally introduced by Kass et al. [16], has been extensively applied in breast ultrasound images' segmentation [14, 17-19] because of its concept of coupling the image data with shape control. It is based on deforming an initial curve towards the region of interest to be detected. An energy function could be associated with the curve, so the problem of finding an object boundary could be cast as an energy minimization process. Typically, curves could be affected by both an internal energy and an external energy as shown by the following equation:

$$E = \int_0^1 (E_{\text{int}}(v(s)) + E_{ext}(v(s)))ds \qquad (7)$$

E_{int} represents the internal energy coming from the curve itself. However, E_{ext} denotes the external energy computed from the image data.

Figure 4, shows an example of segmented ultrasound breast lesion (figure 4a), and the extracted region of interest (figure 4b) used to compute the improved SGLDM.

The key idea of our improved SGLDM is as follows: First, we calculate the co-occurrence matrix of the image shown in figure 4b, that is to say, with Ng=256. After that, we eliminate the rows and columns of the co-occurrence matrix corresponding to all gray level values comprised between 255 and the maximum gray level value present in the region of interest. Thus, we obtain the improved co-occurrence matrix that corresponds to the whole lesion.

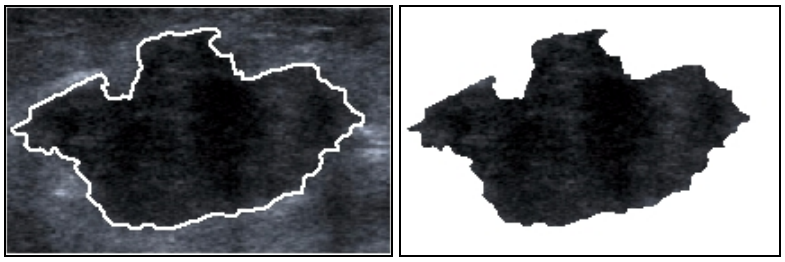
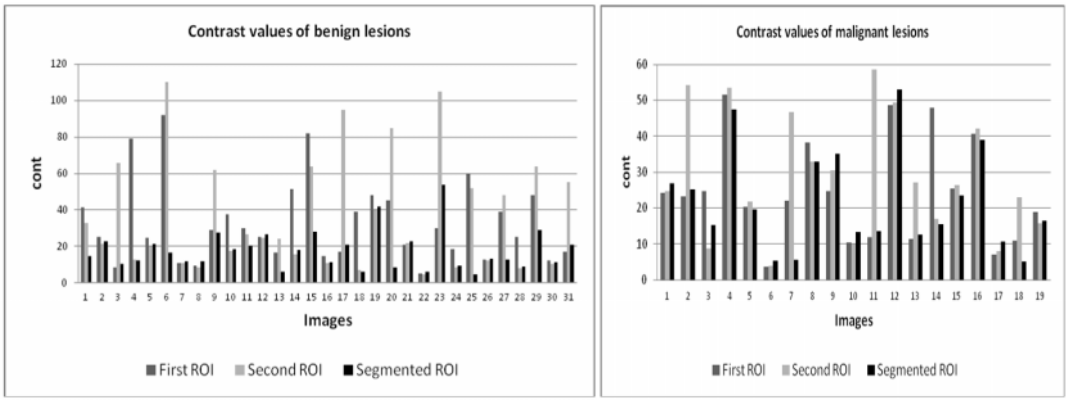


Figure 4. Example of segmented ultrasound breast image
(a) Contour of the lesion, (b) Extraction of the region of interest

3. RESULTS AND DISCUSSION

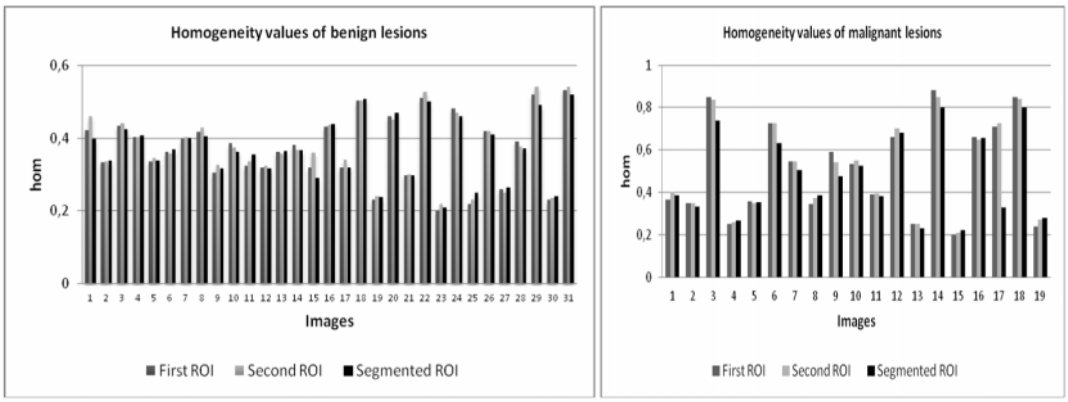
Six Haralick's descriptors for SGLD matrix computation were calculated for both benign and malignant lesions in this study. For that raison, a displacement vector of $d = 1$ is set in this analysis in order to preserve the complexity of spatial relationships. In addition, to eliminate the attenuation effect during the ultrasound transmittance and reflection, the final choice for the orientation was $\Theta = 0°$.

We start first by demonstrating that the selection of the region of interest is operator dependant. In fact, for the 50 breast ultrasound lesions, two rectangle region of interest were selected by two practitioners differently, as well as a region of interest was extracted on the basis on the segmentation using active contour method. In each case, we calculated the values relating to the contrast (figure 5), homogeneity (figure 6), energy (figure 7), entropy (figure 8), mean (figure 9), and variance (figure 10).



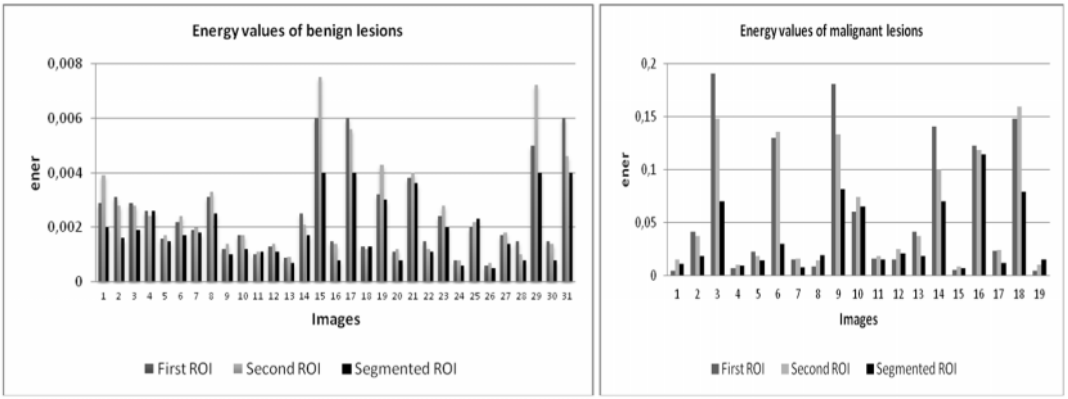
(a) (b)

Figure 5. Contrast values for three ROI of
(a) benign lesions and (b) malignant lesions



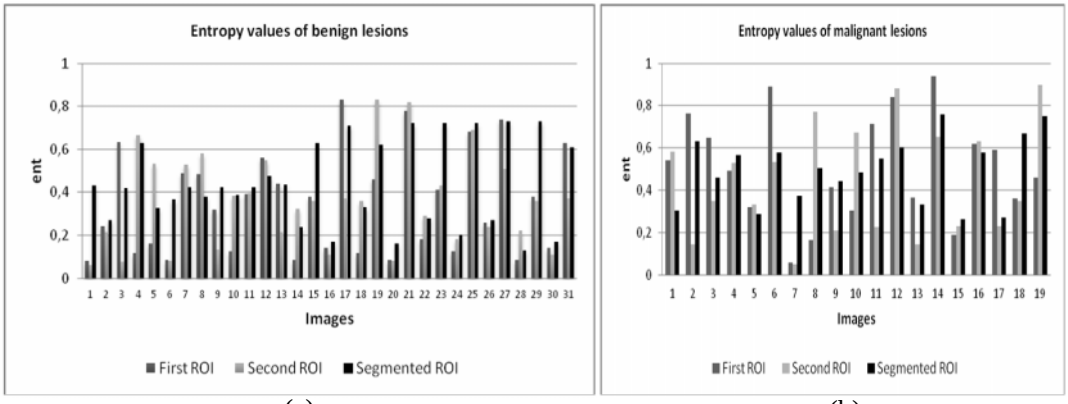
(a) (b)

Figure 6. Homogeneity values for three ROI of
(a) benign lesions and (b) malignant lesions



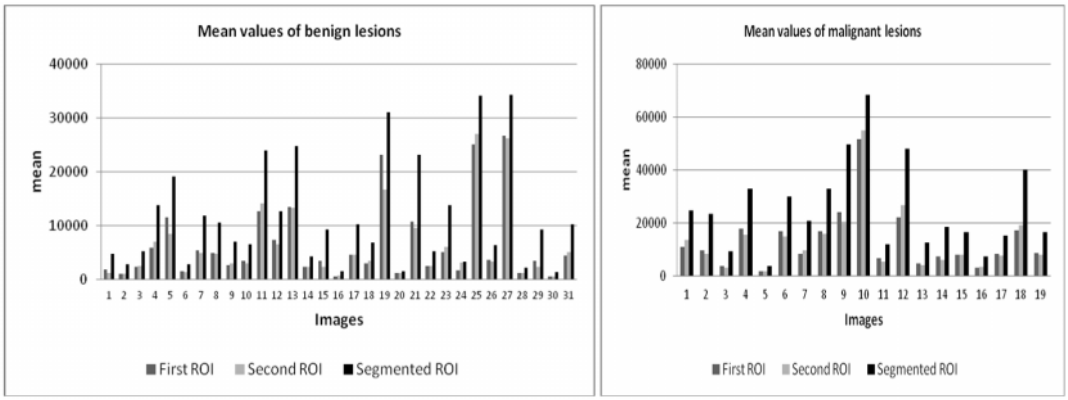
(a) (b)

Figure 7. Energy values for three ROI of
(a) benign lesions and (b) malignant lesions



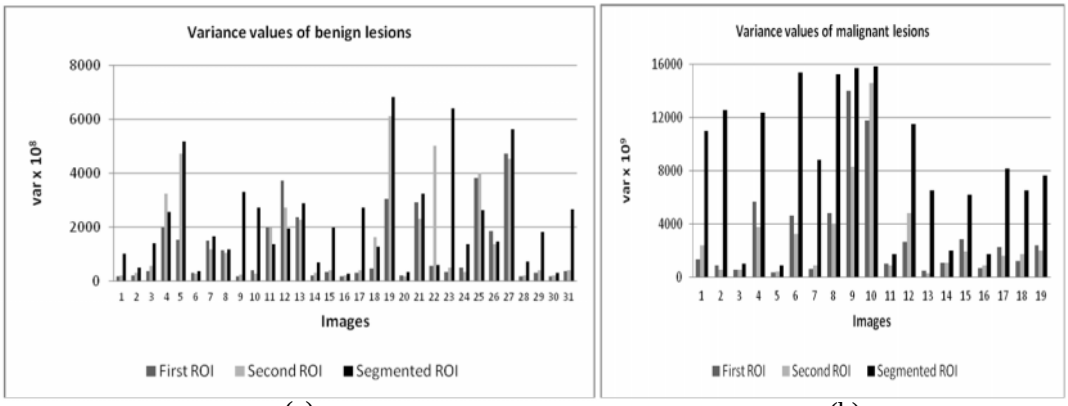
(a) (b)

Figure 8. Entropy values for three ROI of
(a) benign lesions and (b) malignant lesions



(a) (b)

Figure 9. Mean values for three ROI of
(a) benign lesions and (b) malignant lesions



(a) (b)

Figure 10. Variance values for three ROI of
(a) benign lesions and (b) malignant lesions

By examining the obtained results, we can see clearly that, for each parameter, the values extracted from each region are variable for the same lesion. This remarkable disparity is due to the variation of the selected region of interest, except for a few cases where the lesion has a very regular shape. This plainly proves that the calculation of textural features depends strongly on the operator, and subsequently affects the results precision. It is for this reason that we tried to make it ideally invariant by applying segmentation method.

Table 1. Values of six texture parameters of benign and malignant tumors for three regions of interest

	Histology	**mean**	**sd**	**min**	**max**
cont	B1	32.7596	22.2426	5.0102	91.9111
	B2	36.8975	31.0595	4.5071	110.2816
	B3	17.7657	10.8122	4.5147	54.8710
	M1	24.5461	14.5755	3.5702	51.5795
	M2	29.1559	17.1735	3.7686	58.5415
	M3	21.8610	14.0358	5.3344	53.3374
hom	B1	0.3708	0.0909	0.2059	0.5342
	B2	0.3771	0.0902	0.2246	0.5490
	B3	0.3687	0.0839	0.2153	0.5248
	M1	0.5136	0.2260	0.2024	0.8860
	M2	0.5169	0.2177	0.2108	0.8561
	M3	0.4730	0.1928	0.2281	0.8010
ener	B1	0.0024	0.0015	0.0006	0.006
	B2	0.0025	0.0017	0.0007	0.0075
	B3	0.0018	0.0011	0.0005	0.004
	M1	0.0616	0.0660	0.0042	0.191
	M2	0.0578	0.0549	0.0084	0.159
	M3	0.0354	0.0326	0.0071	0.114
ent	B1	0.3433	0.2364	0.0801	0.8324
	B2	0.3570	0.2177	0.0623	0.8357
	B3	0.4365	0.1958	0.13	0.7309
	M1	0.5094	0.2519	0.0637	0.9411
	M2	0.4434	0.2613	0.05	0.9006
	M3	0.4951	0.1578	0.2641	0.7603
mean	B1	7096.0682	4.2743e+003	450	26600
	B2	6808.8986	4.0062e+003	508	27030

	B3	9731.9537	9.0859e+003	1350	34258
	M1	12988.57	11373.17	1575	51660
	M2	12907.57	12193.37	1704	54943
	M3	25329.05	481252	3795	68300
var	B1	1159.84e+08	1300.14e+08	155.14e+08	4778e+08
	B2	1523.98e+08	1730.47e+08	168.23e+08	6809e+08
	B3	2149.32e+08	1768.08e+08	275.89e+08	6100e+08
	M1	3099.97e+09	3801.01e+09	325.688e+009	13958e+09
	M2	2828.39e+09	3460.88e+09	301.257e+009	14576e+09
	M3	8437.64e+09	5304.77e+09	853.568e+010	15807e+09

sd = standard deviation value, min = minimum, max = maximum, B1 = first region of interest of benign lesion, B2 = second region of interest of benign lesion, B3 = segmented region of interest of benign lesion, M1 = first region of interest of malignant lesion, M2 = second region of interest of malignant lesion, M3 = segmented region of interest of malignant lesion

In order to generalize our results, we present in Table1 the mean, standard deviation, minimum, and maximum values of texture parameters computed from the three region of interest of all benign and malignant lesions.

By comparing the values of Table 1 for each parameter, we notice the difference in the mean, standard variation, minimum and maximum values between the three regions of interest either in the case of benign or malignant lesions. This difference may influence the diagnosis because we cannot establish a well determined threshold for the classification of lesions.

We can so note the importance of our improved SGLDM method especially in the differentiation between lesions. Consequently, this method allows improving radiologist's accuracy in distinguishing benign from malignant breast masses. As well as, this method can be integrated in the process of the computer aided diagnosis as a texture feature allowing thus the classification of the breast ultrasound lesions in an automated manner.

4. CONCLUSIONS

In this paper we presented an improved SGLDM method to extract textural feature based on the whole segmented lesion using active contour method. According to the experimental results, we showed that our method outperforms the existing SGLDM method, which is operator dependant, in terms of accuracy in calculating textural features. Consequently, we may determine a definite threshold necessary for classification, and we can subsequently improve breast diagnosis for distinguishing benign from malignant breast masses.

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