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Texture Descriptors to Improve Automatic Breast Tumor Segmentations in Ultrasound Images

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Keywords: Ultrasound texture analysis, Breast tumor segmentation, Ultrasound contrast enhancement

Abstract

Texture descriptors have been widely used to improve the results of automatic breast tumor segmentations in ultrasound images. In this work we present a comprehensive evaluation of the ability of different types of texture descriptors to enhance the contrast between breast tumors and healthy tissue in ultrasound images and how they affect the results of automatic tumor segmentation. We evaluated descriptors extracted from the analysis of the histogram, co-occurrence and run-length matrices. The contrast between the tumor region and normal breast tissue was evaluated using the signal to noise ratio (SNR), contrast to noise ratio (CNR), histogram intersection and Minkowski-form Distance between the tumor region and normal tissue histograms. We have implemented a probabilistic segmentation method in order to evaluate the changes in the accuracy, sensitivity, specificity, positive predictive value (PPV) and negative predicted value (NPV) of the method when using different texture descriptors. The Short Run Emphasis of the run-length matrix showed significantly better results in the automatic segmentation of breast tumors with values of 91.96%, 88.58%, 95.99%, 96.34% and 87.58% respectively.

Keywords: Ultrasound texture analysis, Breast tumor segmentation, Ultrasound contrast enhancement

Introduction

Since breast cancer has become the number one cause of death among women around the world, it is very important to have fast and accurate diagnostic methods to improve the prognosis of the patient[1]. Although biopsy is the gold standard for cancer diagnosis, minimal invasion methods for diagnosis are preferred in order to reduce further complications. Mammography and ultrasound are the two main medical imaging modalities for breast tumor screening, several diagnostic methods using ultrasound images have been proposed. Currently ultrasound is responsible for about one in five of all diagnostic images[2], the expert ultrasonographer estimates the malignity of a tumor mainly from its shape and echogenicity (which is an indication of the tumor density).
The visualization of lesions in ultrasound breast images is a difficult task due to some intrinsic characteristics of the images like speckle, acoustic shadows and blurry edges[3]. In this work we report a comprehensive analysis of textural features which improve the outcome of automatic breast tumor segmentation in ultrasound images. Accurate automatic segmentation of breast tumors can help the experts to achieve faster diagnoses, and it's a key stage of fully automatic systems for breast cancer diagnosis using ultrasound images.

Texture analysis refers to the characterization of regions in an image by their texture content, quantifying intuitive qualities described as roughness, smoothness, silkiness and bumpiness[4]. In ultrasound images echo patterns are generally referred to as textures[5]; a good breast tumor segmentation method in ultrasound images should take into account texture features in order to differentiate tumors from other objects with similar gray intensities, like glands and acoustic shadows[6], however texture analysis in ultrasound images is not an easy task and many texture metrics have been used to model the echo patterns in breast tumors. Several automatic and semi-automatic segmentation methods using pixel intensity along with texture information have been proposed[6]. Some of these methods use first-order texture descriptors obtained from histogram statistics[6,7], but these descriptors are not able to give a good texture description in ultrasound images because they do not take into account the spatial relation between pixels and gray-levels[8]; because of this, other proposed methods use second-order texture descriptors extracted from co-occurrence matrices statistics[9], but the computational cost for computing the co-occurrence matrix is very high and much more demanding while working in per-pixel computation[10]. Other texture descriptors extracted from run-length matrices statistics have been used for breast tumor classification in ultrasound images.

Texture is a rich source of visual information and there are a number of methods for texture representation, because of this, it is difficult to define the properties that can be used to effectively distinguish textures found in a given image[11]. On the other hand, image enhancement is key to improve the visual appearance of an image and make it more pleasant for human interpretation or more applicable in some special fields, such as computer vision and image segmentation[12,13]. For these reasons, it is important to evaluate which texture descriptor is the one that significantly enhances the contrast of the images and how this improves the outcome of an automatic segmentation method. In this work we report an extensive evaluation of the effects of texture descriptors (extracted from histogram statistics, co-occurrence matrices statistics and run-length matrices statistics) on the contrast between the tumor region and the surrounding tissue in breast ultrasound images and how this improves the results of an automatic segmentation algorithm. Except for the work done by Liao et al[5], where they compare the ability of different texture descriptors extracted from co-occurrence matrices statistics to enhance the contrast between the tumor region and the surrounded tissue and how it affects the results of manual and automatic segmentations, there is no related work that evaluates the ability of different texture descriptors, extracted from first and second order statistics, to improve the automatic segmentation of tumors in breast ultrasound images. To evaluate the ability of these descriptors to enhance the contrast between the tumor region and the healthy tissue, we obtained a texture image using per-pixel computation using different texture descriptors and compare the signal to noise ratio (SNR), contrast to noise ratio (CNR), histogram intersection and Minkowski-form Distance between the tumor region and healthy tissue histograms in each image. We have also evaluated the ability of these descriptors to improve the segmentation results; we implemented a probabilistic segmentation method based on the work of Madabushi et al[6] and compared the accuracy, sensitivity, specificity, positive predictive value (PPV) and negative predicted value (NPV) of the method when using different texture descriptors. We have found that the short run emphasis of the run-length matrix significantly improves the segmentation results previously reported by other autors[5,6].

Materials and Methods

A data base of 30 breast ultrasound images with a lesion were acquired with a GE Healthcare Voluson 73 in the Changhua Christian Hospital. The images were processed in the open source software itk-SNAP for image enhancement and semi-automatic segmentation supervised by an expert sonographer[14].

Texture Analysis

Here we evaluate texture descriptors extracted from histogram statistics, co-occurrence matrices statistics and run-length matrices statistics.

First-order texture descriptors are extracted from the original image values; they do not consider the spatial relationships with neighborhood pixels[15]. The most frequently used first-order texture descriptors are central moments of the histogram[16]. These descriptors have been used for the segmentation and classification of breast tumors in ultrasound images; Huang et al[7] use the Mean and Entropy of the histogram to characterize the texture of breast tumors, also the Kurtosis and Skewness of the histogram have been used for tumor classification by Pilouras et al[17]. Another first order texture descriptor, extracted from the image original intensity values, used for automatic breast tumor segmentation in ultrasound images is the difference of the intensity of each pixel with the mean of its neighborhood[6].

The gray-level co-occurrence matrix describes how frequently two gray-levels appear in a window separated by a given distance and a given angle[16]. Second-order texture descriptors computed from the analysis of the co-occurrence matrices have been proposed by Haralick[18]. Some of these texture descriptors have been used for the segmentation and classification of breast tumors; Liu et al[9] use the entropy and contrast of the co-occurrence matrix for breast tumor segmentation. Liao et al[5] evaluate the ability of the homogeneity, contrast, energy and variance of the co-occurrence matrix to enhance the contrast of tumors in breast ultrasound images, concluding that the variance of the co-occurrence matrix is the best texture descriptor of the four to be used in breast tumor contrast enhancement in ultrasound images. Although these descriptors take into account the spatial relationship between pixels the computational cost of computing the co-occurrence matrix is very high compared to first order descriptors[10].

Another method to characterize texture that also takes into account the spatial relationship between pixels is based on run-lengths of image gray-levels, where the run-length matrix of an image is defined as the number of runs with pixels of equal gray level and a given run-length[15]; although these descriptors have not been widely used as an effective texture classification and analysis method, it has been demonstrated by Tang et al[19] that there is rich texture information contained in this matrices. Galloway[20] proposed five texture descriptors based on the analysis of run-length matrices: short run emphasis (SRE), long run emphasis (LRE), gray-level nonuniformity (GLN), run-length nonuniformity (RLN) and run percentage (RP); these descriptors have been used for the classification of malignancy of breast tumors in ultrasound images[17,21,22]. A list of the texture descriptors evaluated in this work, extracted from histogram, co-occurrence and run-length statistics is shown in table 1.

Table 1. List of evaluated texture descriptors.

First order	Mean	Huang et al[7]
	Entropy	Huang et al[7]
	Kurtosis	Pilouras et al[17]
	Skewness	Pilouras et al[17]
	Mean Difference	Madabhushi et al[6]
Co-occurrence	Entropy	Liu et al[9]
	Contrast	Liu et al [9]
	Homogeneity	Liao et al[5]
	Energy	Liao et al [5]
	Variance	Liao et al [5]
Run-length	Short Run Emphasis	Lefebvre et al[22]
	Long Run Emphasis	Lefebvre et al [22]
	Gray-Level Nonuniformity	Murmis et al[21]
	Run-length Nonuniformity	Murmis et al [21]

Segmentation Method

Because of inherent artifacts in breast ultrasound images such as speckle and blurry edges, the segmentation of tumors is not an easy task[3]. Several works have been done in order to create semi-automatic and automatic methods. Based on the literature, these methods can be divided in two groups; thresholding based methods and classifiers based methods. The thresholding based methods have low computational cost and usually use only gray-level intensities of the pixels to segment de image[3,7,23]. The classifier based methods are more robust since they use more than one feature for classification, but the implementation and the computational cost increments considerably compared with thresholding based methods[1,6,9,24]; the image features used for classifier based methods should be appropriately selected according to the application, texture information might be suitable for ultrasound images[3].

We have implemented an automatic segmentation method based on the work of Madabhushi et al[6]. This method is based on a region-growing algorithm applied to a probability image instead of an intensity image. The probability image is constructed with the probabilities of each pixel of belonging to the tumor region, based on the pixel intensity and texture features. Two density probability functions (*pdf*) are constructed using the gray-level intensity and texture features from previously segmented tumors; the joint probability of the two *pdfs* is computed as the pixel probability to belong to a tumor.

Most of the proposed methods for tumor segmentation in breast ultrasound images use a pre-processing step to obtain more homogenous regions and enhance the contrast between the tumor and the surrounding tissue. For contrast enhancement some works used the stick method[3,23,24], but Madabushi et al[6] proposed the use of histogram equalization because it is a fast method with good results in tumor enhancement. To obtain more homogenous regions a Gaussian filter was used by Chen et al[3] and a Butterworth filter was used by Madabhushi et al[6], but Abd et al[25] showed that the Gaussian Anisotropic Filter has better results in ultrasound images since it preserves boundaries. Based on this, we implemented a pre-processing step to obtain a contrast enhanced intensity image using histogram equalization and then a Gaussian Anisotropic Filter to obtain more homogenous regions while preserving the edges.

To obtain a texture image using the texture descriptors listed in table 1 we use per pixel computation, with the parameters proposed in the different cited works. Because texture parameters in ultrasound images characterize the acoustic properties of the tissue[22], the texture image was computed from the original image without any pre-processing step to avoid elimination of any texture related information.

After computing the probability image, using the pre-processed intensity and texture joint probability as explained before, the method use a region growing algorithm on the probability image to obtain the region that belongs to the tumor. To include one pixel t inside the tumor region T it should satisfy two conditions: First, the probability of the pixel of belonging to the tumor $I_p(t)$ should be inside a range of values between the mean of the tumor region probability J_{C_0} by upper and lower thresholds β_1, β_2; second, at least one pixel in the immediate neighborhood $N_t(t)$ of the pixel t should has been included already in the tumor region T; these conditions are shown in equation 1. The seed point of the region is automatically determined by the method using the probability of each pixel, along with spatial information about the potential seed; you can find the complete description of the method in the article published by Madabhushi et al[6]

$$t \in T \Leftrightarrow (\beta_1 J_{C_0} \leq I_p(t) \leq \beta_2 J_{C_0}) \;\&\&\; (T \cap N_t(t) \neq 0) \tag{1}$$

where t is the pixel to be included in the tumor region, T is the tumor region, J_{C_0} is the mean probability of T, β_1 and β_2 are empirically selected thresholds and $N_t(t)$ is the immediate neighborhood of t.

Experiment and Results

Contrast enhancement using texture descriptors

Evaluation of contrast enhancement can be done with different indices, there is no standardized solution for this; therefore, it is important to compute several indices for this purpose, in order to have a good contrast enhancement evaluation[26]. To evaluate the ability of the texture descriptors listed in table 1 to enhance the contrast between the tumor region and the surrounding tissue we used the signal to noise ratio (SNR) and the contrast to noise ratio (CNR) both used by Liao et al[5].

$$SNR = \frac{\mu_{ROI}}{\sigma_{ROI}} \tag{2}$$

$$CNR = \frac{|\mu_{ROI} - \mu_{Background}|}{\sigma_{ROI} + \sigma_{Background}} \tag{3}$$

where μ_{ROI} and $\mu_{Background}$ are mean brightness values of the tumor region (ROI) and the tissue (Background) respectively, and σ_{ROI} and $\sigma_{Background}$ are the standard deviation of the ROI and the background respectively.

In addition to the SNR and CNR we computed the Minkowski-form distance (MD) and the histogram intersection (INT) between the ROI and background regions as similarity measurements between histograms. The Minkowsky distance is often used for computing dissimilarities between histograms[27]. The intersection of the histograms is a useful similarity measurement between two histograms when the number of pixels between regions is different, it is well suited to deal with scale changes[28].

$$MD(H_{ROI}, H_{Background}) = \left(\sum_i \left|H_{ROI}(i) - H_{Background}(i)\right|\right) \quad (4)$$

$$INT(H_{ROI}, H_{Background}) = 1 - \frac{\sum_i \min(H_{ROI}(i), H_{Background}(i))}{\sum_i H_{Background}(i)} \quad (5)$$

where H_{ROI} and $H_{Background}$ are the normalized histograms of the ROI and the background.

Along with contrast enhancement, another important aspect to take into account when using texture analysis for image segmentation is the ability of the descriptor to preserve the edges of the structures we want to segment[5]. To evaluate this, we used the edge preservation index (EPI) defined as

$$EPI = \frac{\sum|p_T(i,j) - p_T(i-1, j+1)|}{\sum|p_o(i,j) - p_o(i-1, i+1)|} \quad (6)$$

where $p_T(i,j)$ is the value of the texture image pixel and $p_o(i,j)$ is the value of the original image; $p_T(i,j)$ and $p_o(i,j)$ are in the edge area, previously segmented in the original image[29].

We compare the SNR, CNR, MD, INT and EPI of the original images with the texture images obtained using per-pixel computation with the descriptors listed in table 1. Table 2 shows the results of MD, INT, SNR, CNR and EPI for the original image, while table 3 shows which texture descriptors improve each contrast index. The results for the pre-processing stage used in the segmentation algorithm to obtain an intensity image with a higher contrast are also shown in table 3.

The first order descriptor that obtained better results enhancing the image was the Mean of the histogram with higher values of MD, INT and CNR than the original image, however the SNR was lower than in the original image and the ability to preserve borders was low; the SNR and the EPI were improved by the Entropy and Mean Difference descriptors respectively, however the other contrast enhancement indices had no good results using these descriptors.

The results also show that using second order descriptors based on the co-occurrence matrix for image enhancement are not useful since none of the texture descriptors proposed by Haralick[18] are able to enhance the contrast of the image. Although none of these descriptors improve the contrast of the image, the Homogeneity of the co-occurrence matrix had higher values in all indices than the other co-occurrence based descriptors. Except for the Variance and Energy, all the Haralick texture descriptors improved the SNR significantly but the MD, INT, CNR and EPI were reduced considerably using these descriptors. Looking at equation 2 a higher SNR value may imply two things, the mean gray-level of the region increased and/or the standard deviation of the region decreased, making the region brighter and/or more homogenous, but if the contrast between the region and the background is diminished the visualization of the region of interest is going to be more difficult, since the mean gray-level and the homogeneity of the regions is very similar; in figure 1 is shown how a breast tumor with high SNR in an ultrasound image does not imply a better visualization of the lesion, the original image has a SNR value of 1.4940 and a CNR value of 1.4882 and the texture image, obtained using the correlation of the co-occurrence matrix as texture descriptor, has a SNR value of 3.2322 and a CNR value of 0.0744.

Table 3 shows that of all the Run-length texture descriptors the SRE of the run-length matrix have better results improving the MD, INT, SNR and CNR of the image; this texture feature is also the one that enhances the

Minkowski-form distance and the histogram intersection the most, making easier the differentiation between regions using their probabilities, since the normalized histogram can be used as the probability density function of each gray-level to belong to a region[30]. As the Haralick texture descriptors, none of the run-length texture descriptors was able to preserve borders, decreasing the EPI significantly; in fact, of all the texture descriptors listed in table 1, the only one able to preserve edges was the difference of the mean[6]

Table 2. Original image contrast indices

MD	INT	SNR	CNR	EPI
1.4136 ±0.3264	0.2932 ±0.1632	1.7450 ±0.5285	1.0784 ±0.3316	1 ±0

Table 3. Texture descriptors than enhance the contrast

Index	Type		Descriptor	Value
MD	Texture	Histogram	Mean	1.5460 ±0.3075
		Haralick	--	--
		Run-length	LRE	1.4811 ±0.3119
			SRE	1.6217 ±0.2944
	Intensity		Filter	1.4953 ±0.3132
			Filter + Equalization	1.5383 ±0.3067
INT	Texture	Histogram	Mean	0.2270 ±0.1537
		Haralick	--	--
		Run-length	LRE	0.2594 ±0.1559
			SRE	0.1892 ±0.1472
	Intensity		Filter	0.2524 ±0.1566
			Filter + Equalization	0.2308 ±0.1534
SNR	Texture	Histogram	Entropy	3.3629 ±1.0537
			Kurtosis	1.9337 ±0.5872
			Skewness	2.4845 ±0.7100
			Std	2.1388 ±0.5796
		Haralick	Contrast	1.8608 ±0.5232
			Correlation	3.6850 ±0.9207
			Homogeneity	4.0034 ±0.9603
			Variance	1.7103 ±0.3714
		Run-length	GLN	2.6275 ±0.8319
			RLN	2.2124 ±0.4260
			SRE	3.3263 ±1.0729
	Intensity		--	--
CNR	Texture	Histogram	Mean	1.2495 ±0.3713
		Haralick	--	--
		Run-length	SRE	1.2144 ±0.3924
	Intensity		Filter	1.1682 ±0.3610
			Equalization	1.1105 ±0.3408
			Filter + Equalization	1.1682 ±0.3610
EPI	Texture	Histogram	Difference	1.6522 ±0.2802
		Haralick	--	--
		Run-length	--	--
	Intensity		Equalization	1.7296 ±0.2863
			Filter + Equalization	1.4429 ±0.3702

-- Indicates that none of the descriptors in that category improved the contrast index.

Figure 2 shows a breast tumor ultrasound image, the pre-processed intensity image and texture images obtained by per-pixel computation using the Mean of the histogram, the Homogeneity of the co-occurrence matrix and SRE of the run-length matrix texture descriptors, while figure 3 shows the normalized histograms of the background (red) and the tumor region (blue) of each image in figure 2.

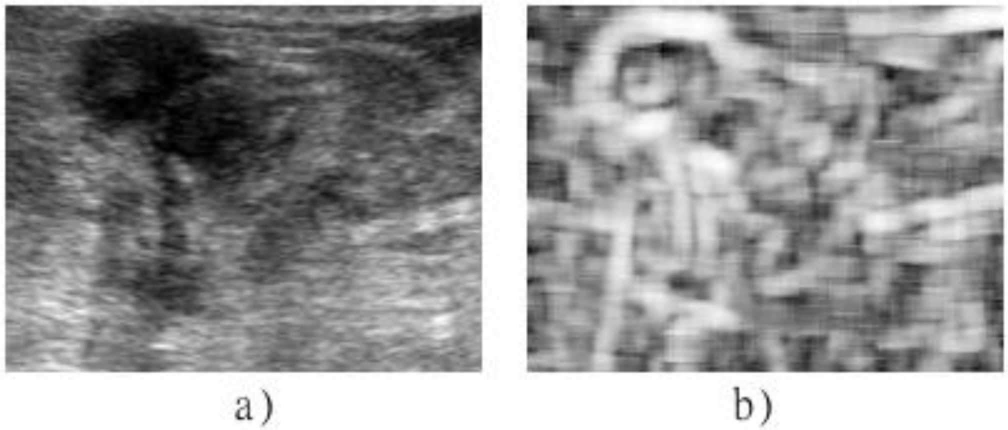

Figure 1. Comparison of lesion visualization with different SNR values a) original image and b) texture image obtained with the correlation of the co-occurrence matrix.

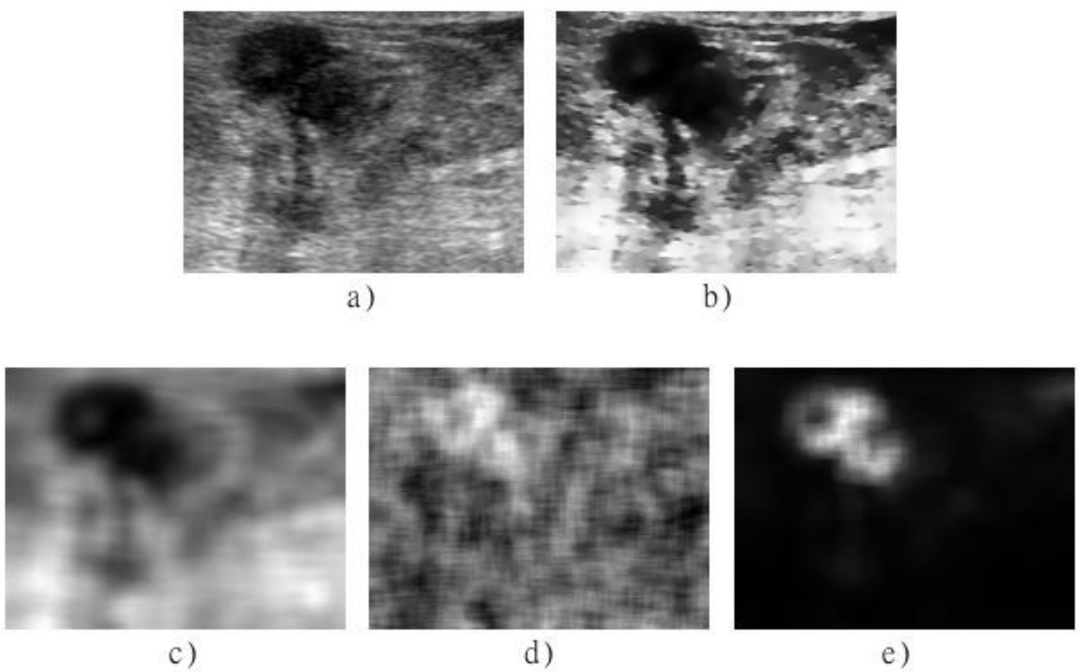

Figure 2. Textural analysis of breast ultrasound images. a) original ultrasound image, b) pre-processed intensity image, c) mean of the histogram texture image, d) Homogeneity of the co-occurrence matrix texture image, and e) SRE of the run-length matrix texture image.

Segmentation evaluation

We used the segmentation method reported by Madabhushi et al[6], which includes a pre-processing step to obtain an intensity image and a texture image in order to build a probability image to segment the tumor with a region growing algorithm. The intensity image is obtained by enhancing the contrast with histogram equalization and homogenizing regions while preserving edges with a Gaussian anisotropic filter. Different texture images were obtained using the texture descriptors listed in table 1. Here we evaluate the results of the segmentation method when using different texture descriptors and compare them with the results without using any texture information (using only the normalized histogram of the intensity image as probability function). To evaluate the segmentation results we used the accuracy, sensitivity, specificity, positive predictive value (PPV) and the negative predictive value NPV[9]:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{7}$$

$$Sensitivity = \frac{TP}{TP + FN} \tag{8}$$

$$Specificity = \frac{TN}{TN + FP} \tag{9}$$

$$PPV = \frac{TP}{TP + FP} \tag{10}$$

$$NPV = \frac{TN}{TN + FN} \tag{11}$$

where TP, TN, FP and FN are the true positive, true negative, false positive and false negative pixels found in the segmentation process. These indices were evaluated for the 30 images using leave-one-out cross-validation. The accuracy is the ratio of correctly classified pixels (true positives and true negatives) in the entire area of the image[31]. The sensitivity and specificity are often used to complement the evaluation of segmentation algorithms, sensitivity is used for measuring how many pixels in the region of interest are correctly segmented, it does not tell anything about how many pixels in the background would be segmented as tumors[32]; the specificity measures how many pixels in the background are correctly excluded and does not tell if a tumor pixel would not be correctly segmented[33]. The positive and negative predictive values are related with the sensitivity, specificity and the size of the tumor region, the predictive values will change between images if the tumor region covers a different percentage of the whole image, it is important to take this into account since breast tumors size change between patients[34]. Table 4 shows the segmentation results using only the original image without any pre-processing (top row) and using the intensity image obtained with histogram equalization and a Gaussian anisotropic filter (bottom row). The pre-processing step was able to improve the segmentation results, making the accuracy, specificity and PPV significantly higher, while the sensitivity and NPV were diminished by 1.24% and 0.54% respectively.

Table 4. Original and Intensity images segmentation results

Image	Accuracy	Sensitivity	Specificity	PPV	NPV
Original	83.89%	86.51%	87.63%	78.94%	87.26%
Intensity	87.13%	85.28%	89.52%	85.96%	86.72%

We also evaluated the ability of the different texture descriptors listed in table 1 to enhance the segmentation results. Almost all of the first order texture descriptors enhanced the segmentation results except for the NPV, which was not improved by any of the texture descriptors. The first order texture descriptor that leads to better segmentation results was the mean of the histogram, having higher percentage of accuracy, sensitivity, PPV and NPV, with values of 90.58%, 89.36%, 94.08% and 87.08% respectively; the higher value of specificity was obtained using the entropy of the histogram, but the difference between the specificity of the mean and the entropy is only of 0.36% making it insignificant; the NPV was diminished by 1.22% using the mean of the histogram. The accuracy, sensitivity and NPV of the segmentations obtained using the Haralick texture descriptors where similar to the ones using the first order descriptors; the higher values of accuracy (90.60%), sensitivity (88.66%) and NPV (86.78%) were obtained with the homogeneity of the co-occurrence matrix; this texture descriptor also improves significantly the specificity (93.84%) and PPV (93.40%) of the segmentation. None of the Haralick texture descriptors was able to increase the NPV value. Using run-length texture descriptors in the segmentation lead to better results in all indices, except for the sensitivity where the mean of the histogram obtained the higher value; the LRE and the SRE were the only texture descriptors of the ones listed in table 1 able to increase the NPV value, having the highest value (87.58%) using the SRE of the run-length matrix; the highest values of accuracy (91.96%), specificity (95.99%) and PPV (95.34%) were also obtained using the SRE of the run-length matrix and although the SRE did not show the highest value in sensitivity, this index was improved by the SRE compared with the segmentation results without any texture information.

Table 5 shows that using the listed texture descriptors along with the pre-processed image the accuracy, specificity and the PPV can be significantly improved, and although, the increase of sensitivity and NPV in the segmentation using texture descriptors is not as significant as in the accuracy, specificity and PPV. Comparing the results shown in table 5 with the results shown in table 4, it can be seen that the segmentation improves significantly when using texture information instead of only using the original image or the pre-processed intensity image. While none of the first order and Haralick texture descriptors were able to increase the NPV value of the segmentation, table 5 shows that the SRE was able to increase it by only 0.32%; although this increment is insignificant, at least this descriptor do not diminish the NPV of the segmentation.

Table 5. Segmentation results using different texture descriptors

Category	Descriptor	Accuracy	Sensitivity	Specificity	PPV	NPV
First Order	Mean	90.58%	89.36%	94.24%	94.08%	86.36%
Haralick	Homogeneity	90.60%	88.66%	93.84%	93.40%	86.78%
Run-length	SRE	91.96%	88.58%	95.99%	96.34%	87.58%

Figure 4 shows the segmentation of a breast tumor in an ultrasound image using different texture descriptors along with the pre-processed intensity image with the probabilistic segmentation method implemented here, it also shows the segmentation results obtained when using only the original intensities of the image and the pre-processed intensity image without any texture information. Table 6 shows the accuracy, sensitivity, specificity, PPV and NPV of the segmented images shown in figure 4.

It can be seen in table 6 that using texture descriptors along with a pre-processed intensity image for breast tumor segmentation in the ultrasound image shown in figure 1a) can upgrade the results considerably. Although the sensitivity and NPV are diminished using the texture descriptors, the difference is insignificant (1% and 0.3% respectively) comparing it with the increase in accuracy, specificity and PPV values (16%, 24% and 34% respectively) using the SRE of the run-length matrix as texture descriptor.

Table 6. Segmentation results for the segmented images shown in figure 4.

Descriptor	Accuracy	Sensitivity	Specificity	PPV	NPV
Original	82.41%	99.75%	74.03%	64.98%	99.03%
Intensity	91.10%	99.49%	85.14%	82.62%	99.57%
Mean	97.96%	98.50%	97.42%	97.39%	98.52%
Homogeneity	95.97%	98.92%	93.96%	92.96%	98.98%
LRE	98.28%	98.74%	98.84%	98.85%	98.72%

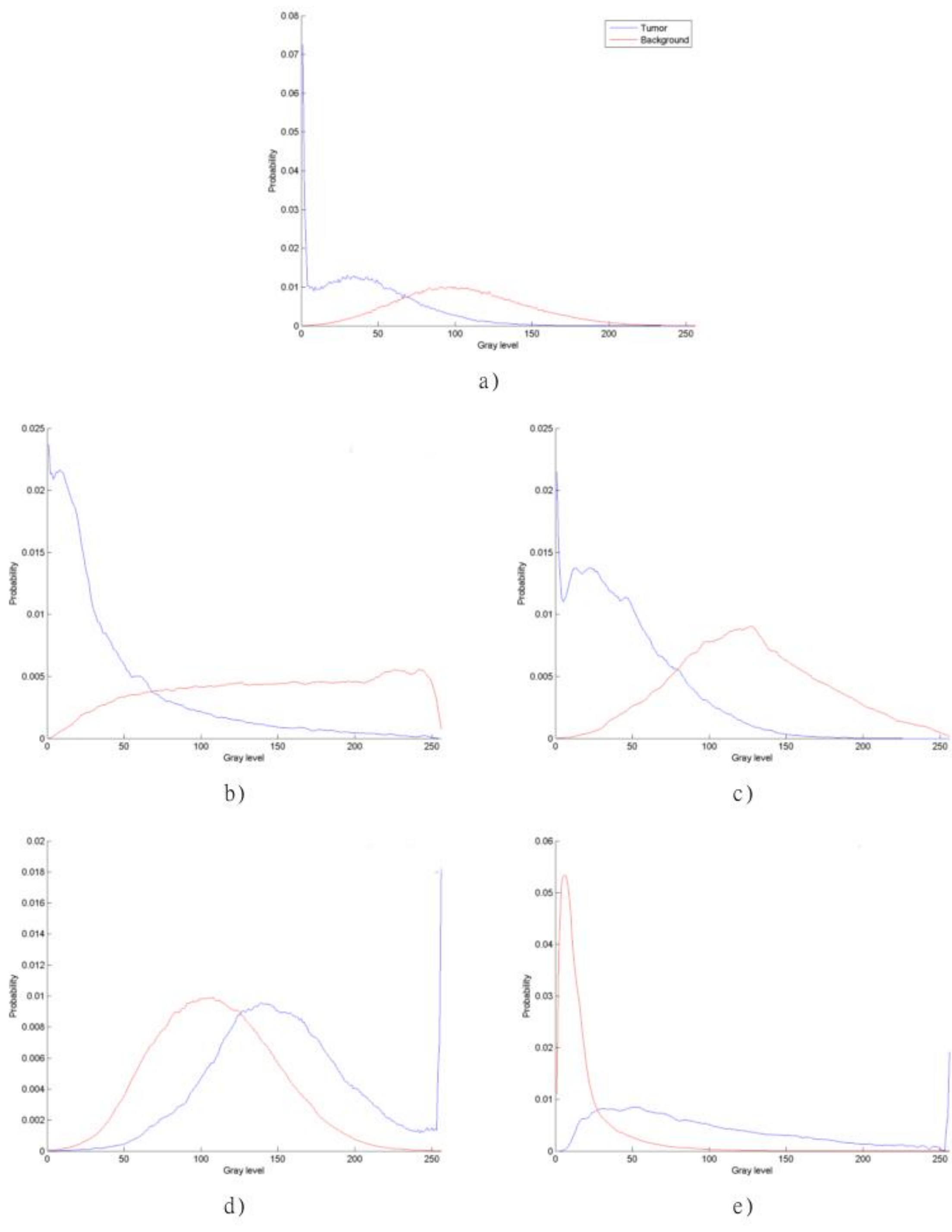

Figure 3. Normalized histograms of textural analysis. a) original ultrasound image, b) pre-processed intensity image, c) mean of the histogram texture image, d) Homogeneity of the co-occurrence matrix texture image, and e) SRE of the run-length matrix texture image.

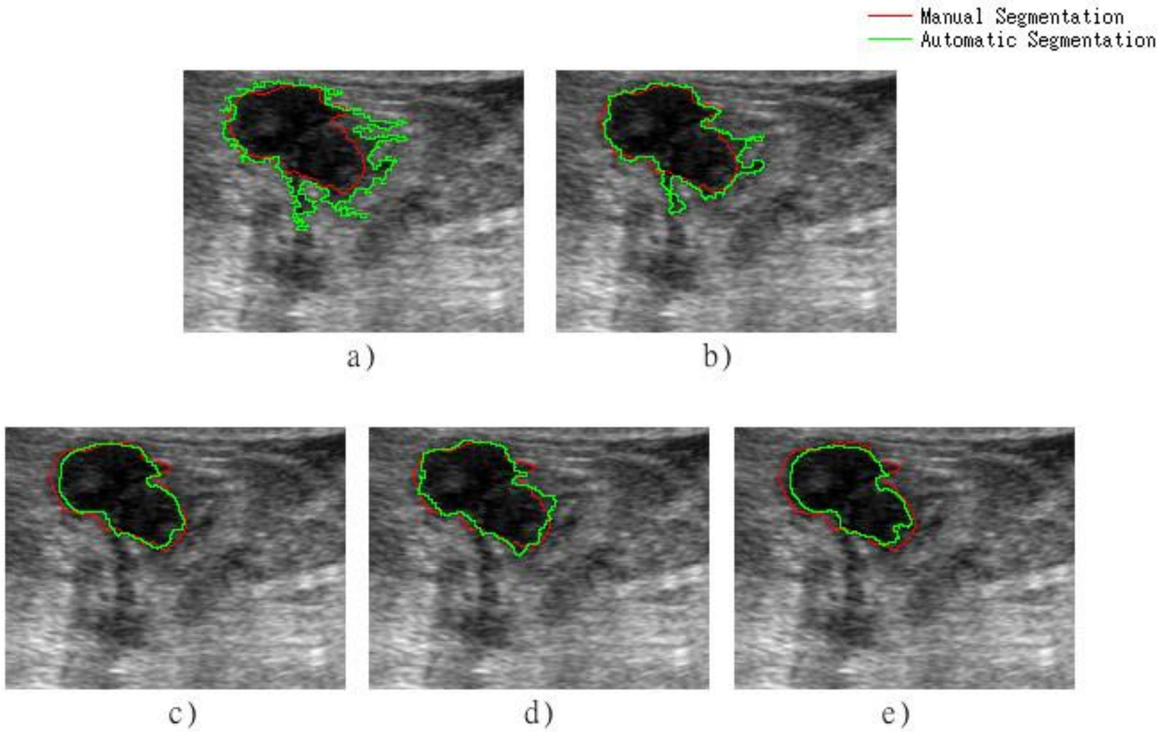

Figure 4. Segmentation of a breast tumor using a) original image, b) pre-processed intensity image c) mean of the histogram, d) homogeneity of the co-occurrence matrix, and e) SRE of the run-length matrix.

Discussion and Conclusion

Texture descriptors have been widely used in breast ultrasound images for tumor segmentation, since they help to differentiate structures with similar gray-level intensities from tumors, such as acoustic shadows[6]. In this work we reported a quantitative evaluation of different texture descriptors in order to find out which one is the most effective to enhance the contrast of the image and which one leads to better segmentation results.

Image quality is a key aspect to consider in ultrasound images since they are affected by many types of artifacts, making it hard for an observer to interpret the images and obtain quantitative and qualitative information from them[35]. Because of the noisy nature of the ultrasound images and the low contrast between breast cancer and surrounding tissue, it is difficult to provide an accurate and effective diagnosis[36]. The ability of different texture descriptors to enhance the contrast between the tumor region and normal tissue was evaluated with five indices (MD, INT, SNR, CNR and EPI). It was shown in the results that some of the texture descriptors listed in table 1 are able to increase one or more of the used contrast indices, and that SRE of the run-length matrix was able to increase all the indices but not the EPI; in fact none of the used texture descriptors, except for the difference of the histogram, was able to preserve edges. It was also shown that the co-occurrence based texture descriptors proposed by Haralick[18] are no good for image enhancement since none of them was able to increase the value of the contrast indices, except for the SNR but this may not lead to a better visualization of the tumor region as can be seen in figure 1. The mean of the histogram also showed good results enhancing the contrast of the image, enhancing almost all of the contrast indices except for the SNR and EPI; this texture descriptor may be used instead of the SRE of the run-length matrix for image enhancement when time is an important factor since first order texture descriptors have lower computational cost than higher order descriptors[17]. The proposed pre-processing intensity step, using histogram equalization and Gaussian anisotropic filtering, showed similar results to the mean of the histogram, but this pre-processing step was able to preserve the edges of the tumor, meaning that it is a good alternative for breast tumor contrast enhancement in ultrasound images.

The segmentation was evaluated using five indices (accuracy, sensitivity, specificity, PPV and NPV), and we use a semi-automatic segmentation supervised by a physician as the ground truth. Table 5 shows that the SRE of the run-length matrix is the texture descriptor, of all listed in table 1, that improves more the segmentation results, having a significant increase in all of the indices used here to evaluate the segmentation, except for the NPV where the increase was not significant but the value was not diminished; it is important to notice that this texture descriptor is also the one that shows better results in contrast enhancement increasing the MD and decreasing the histogram intersection significantly making it easier to differentiate between regions when using the normalized histogram as a probability function. The segmentation results reported in this work show that texture features provide useful information that helps to distinguish between tumors and normal tissue in breast ultrasound images, table 5 shows that the homogeneity of the co-occurrence matrix provides useful information to improve the outcome of the segmentation even though this texture descriptor does not enhance the contrast of the image.

Although different texture descriptors provide different information about the texture of the lesion, in this work the segmentation was made using only one texture feature in order to evaluate its effects accurately. Our results show that run-length texture descriptors lead to the best contrast enhancement and segmentation results. In fact, the results of the segmentation using the SRE of the run-length matrix were significantly better compared with the results reported by Madabhushi et al[6], where they reported 76.07% of TP and 76.06% of TN against 96.34% of TP and 87.58% of TN obtained in this work when using the SRE as texture descriptor; also, the results were better than the ones reported by Liao et al[5], where they reported 95% of TP and 85% of TN when using the variance of the co-occurrence matrix as texture information for their automatic segmentation method. The SRE of the run-length matrix is indicative of fineness or high frequency content in an image region, since a fine texture should contain primarily short runs. The improvement of the segmentation results when using this texture descriptor its them most likely due to its ability to detect differences in the spatial frequencies, of the speckle patterns, of the tumor and the surrounding normal tissue[19].

Declaration of Conflicting Interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Acknowledge

The authors would like to thank the National Council of Science and Technology and the National Autonomous University of Mexico for the support of this work.

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