Tumor Demarcation by using Local Thresholding on Selected Parameters obtained from Co-occurrence Matrix of Ultrasound Image of Breast

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ABSTRACT
Ultrasound imaging (US) is the most widely used and important imaging modality in medical domain. Due to certain artifact such as speckle, segmentation of US image has not remained a trivial task. Two stages segmentation process has been used in this paper to detect the solid mass (cancer) in breast US image. GLCM based texture feature image generation followed by local adaptive thresholding. In first, Correlation, Variance, Sum variance and Sum average texture features for all angular relationships has been implemented on original image to obtain the feature images. In Second, adaptive local thresholdinig algorithm is applied recursively by dividing the feature image into nine sub-images and compared with the result of Otsu's global thresholding technique. Results of our algorithm are better.

Keywords
Ultrasound Image, Gray Level Co-occurrence Matrix, Adaptive Thresholding, Feature Images.

1. INTRODUCTION
Ultrasound imaging (US) is very important medical imaging modality to examine the clinical problems. It has become more popular tool than its counterpart with its noninvasive and harmless nature to diagnose various abnormalities present in the human organs. Ultrasonography is relatively inexpensive and effective method of differentiating the cystic breast masses from solid breast masses. It is also fully established method that gives the valuable information about the nature and extent of solid masses and other breast lesions [1], [2]. Segmentation of US images provides detection of desired region (e.g. defected organs, abnormal masses) and draws the boundary accurately around it. Due to some inherent characteristic artifacts such as attenuation, shadows and speckle noise, the process of segmentation of US images is quite difficult [3]. To acquire the accurate segmentation of US images, removal of speckle is an important task [4]. Texture is one of the important characteristics of an image, concerned with the spatial (statistical) distribution of the gray levels. In general, it provides vital information (structure) to identify the objects and area of interest in an image [5], [6]. Textural properties computed over image are specific to

application domain [7]. In application, such as breast ultrasound imaging, it can be used to distinguish normal tissues from abnormal tissues [8], [9]. Gray Level Co-Occurrence Matrix (GLCM) was first proposed by Haralick [10] is one of the methods to analyze textural characteristics and calculate the texture feature.

The other sections of this paper are organized as follows. In section II, formation of gray level co-occurrences matrix is discussed in detail and usefulness of the four texture features is proven. In section III, local adaptive thresholding technique is used on feature image to obtain the resultant segmented image. Conclusion is provided in section IV.

2. GRAY LEVEL CO-OCCURRENCE MATRIX
In this section, we formally describe and discuss the co-occurrence matrices and four feature functions that are computed over them. These features provides basis to discriminate between patterns present in an image, it further can be used in practical problems. Computation of all derived texture features are based on co-occurrence matrix. Construction of this matrix has depends on three important and closely related factors. These are, gray levels, spatial relationship between gray levels (i.e. distance d between two neighboring gray levels,), and angular relationship between neighboring gray levels (i.e. horizontal (0^0), vertical (90^0), backward diagonal (45^0) and forward diagonal (135^0)). In this paper, all the angular relationship has been considered with $d=1$ to construct co-occurrence matrices. Let I be an image, which is two

dimensional matrix of size $(m\ X\ n)$ containing finite number (Ng) of gray levels $G = \{0, 1, 2, ,3, \cdots, Ng\}$. G has spread across horizontal and vertical spatial domain $D\{M, N\}$, $M = \{1, 2, ,3, \cdots, m\}$ and $N = \{1, 2, ,3, \cdots, n\}$ Texture context information present in an image I is completely represented by the matrix of unnormalized relative frequencies Fij . This is the number of occurrence of pairs of two adjacent gray levels separated by distance *d* in an image, one with level *i* and other with level *j*. Fij for an angles quantized to 45^0 intervals and distance d can be properly defined by:

$$\begin{aligned}
Fij(0^0, d) &= \#\{((k_1, l_1)(k_2, l_2)) \in D \,|\, k_1 - k_2 = 0, \\
&\quad |\, l_1 - l_2 \,| = d, I(k_1, l_1) = i, I(k_2, l_2) = j\} \\
Fij(90^0, d) &= \#\{((k_1, l_1)(k_2, l_2)) \in D \,|\, |\, k_1 - k_2 \,| = d, \\
&\quad l_1 - l_2 = 0, I(k_1, l_1) = i, I(k_2, l_2) = j\} \\
Fij(45^0, d) &= \#\{((k_1, l_1)(k_2, l_2)) \in D \,|\, (k_1 - k_2 = d, \\
&\quad l_1 - l_2 = -d) or (k_1 - k_2 = -d, l_1 - l_2 = d), \\
&\quad I(k_1, l_1) = i, I(k_2, l_2) = j\} \\
Fij(135^0, d) &= \#\{((k_1, l_1)(k_2, l_2)) \in D \,|\, (k_1 - k_2 = d, \\
&\quad l_1 - l_2 = d) or (k_1 - k_2 = -d, l_1 - l_2 = -d), \\
&\quad I(k_1, l_1) = i, I(k_2, l_2) = j\}
\end{aligned} \tag{1}$$

Where # denotes the number of occurrence of pairs (i, j) in the image.

These matrices are symmetric in nature (i.e. $Fij(d, a) = Fji(d, a)$ where d is distance and a is angular relationship). In this paper, we are using symmetric GLCM of normalized frequencies, $p(i, j)$, which is calculated on specified area.

$$p(i, j) = \frac{Fij}{F} \tag{2}$$

Where $p(i, j)$ is normalize frequency entry at the gray level (i, j). Fij is unnormalize frequency entry at the gray level (i, j), F is maximum possible frequency entry of neighboring gray level pairs in the GLCM. (e.g. for 3x3 image, vertical and horizontal direction with d =1 value of F is 12 forward diagonal and backward diagonal with d =1 value of F is 8).

Texture is the property of the region as texture of a point is not possible to calculate. Therefore we are considering the 3x3 window to calculate the texture features on original image [11]. Haralick discussed 14 texture feature in his paper. We found four texture feature gives better result as compare to others. Four texture features have proved their importance in ultrasound image segmentation, are Correlation, Variance, Sum average and Sum variance. Co-occurrence matrix of the 3x3 window (region) is obtained and texture feature is calculated for this matrix, then value of texture feature is applied at the center. This process is repeated for entire image and feature image is obtained. Four texture features are described as follows.

$$Correlation = \frac{\sum_{i=1}^{Ng} \sum_{j=1}^{Ng} (ij)\, p(i, j) - \mu_x \mu_y}{\sigma_x \sigma_y} \tag{3}$$

Where, μ_x , μ_y , σ_x and σ_y are mean and standard deviation of co-occurrence matrix, row and column wise respectively.

Using correlation feature, we are measuring the linear dependencies of gray levels. The abnormal (mass) regions in US images consist of mostly constant (homogeneous) gray levels plus some additive noise as compare to other regions of the image [3], [7]. Since noise samples are mostly uncorrelated, the correlation features for the abnormal region having less value as compared to normal region. Boundary between normal and abnormal region of a feature image is clear than original image. Original image and Correlation feature images for all angular relationship are shown in the Fig 1 and Fig.2 respectively.

$$Variance = \sum_{i=1}^{Ng} \sum_{j=1}^{Ng} (i - \mu)^2\, p(i, j) \tag{4}$$

Where, μ is mean of the co-occurrence matrix

$$Sum\ \ Variance = \sum_{i=2}^{2Ng} (i - f5)^2\, p_{x+y}(i) \tag{5}$$

Where,

$$Sum\ \ Entropy\,(f5) = -\sum_{i=2}^{2Ng} p_{x+y}(i) \log(p_{x+y}(i))$$

For the course texture regions in an image, there will be more entries of smaller magnitude in the co-occurrence matrix as compared to fewer entries of larger magnitude for smooth region. Entries for smooth region are concentrated along the diagonal of the co-occurrence matrix. Variance and Sum variance feature give greater values for homogenous region as compared to non-homogenous region to be entered at center of the image. Therefore, these features have great ability to discriminate between the homogeneous and non-homogeneous region. Feature image of Variance and Sum variance is shown in Fig.3 and Fig.4 respectively.

$$Sum\ \ Average = \sum_{i=2}^{2Ng} i p_{x+y}(i) \qquad (6)$$

Where,

$$p_{x+y}(k) = \sum_{\substack{i=1 \\ i+j=k}}^{Ng} \sum_{j=1}^{Ng} p(i,j) \qquad k = 2,3,......,2Ng$$

Sum average feature is focusing on the values around the diagonal of the co-occurrence matrix. Feature value of brighter homogeneous region is greater than the darker homogeneous region. This feature removes the noise but blur the boundary between defected and normal region [12]. The feature image obtained is brighter than the original image and shown in Fig.4.

Fig 1: Original ultrasound image with abnormal mass present in the middle

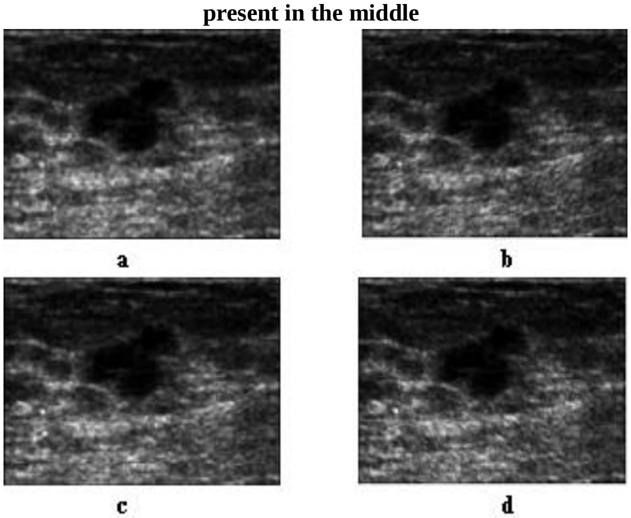

Fig 2: Correlation Feature : (a) 0^0 relationship (b) 45^0 relationship (c) 90^0 relationship (d) 135^0 relationship

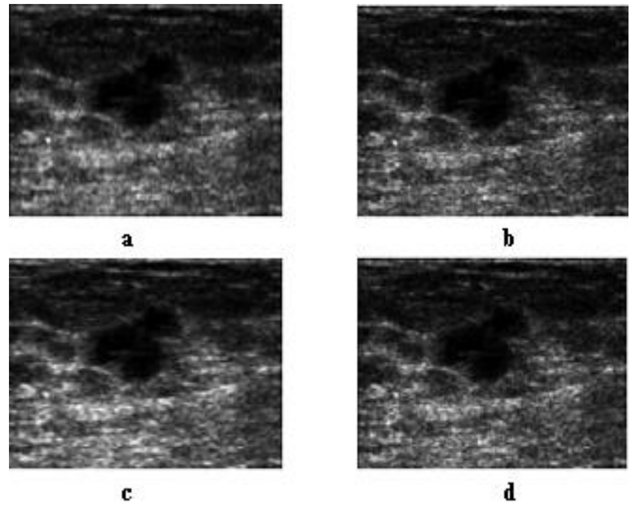

Fig 3: Variance Feature: (a) 0^0 relationship (b) 45^0 relationship (c) 90^0 relationship (d) 135^0 relationship

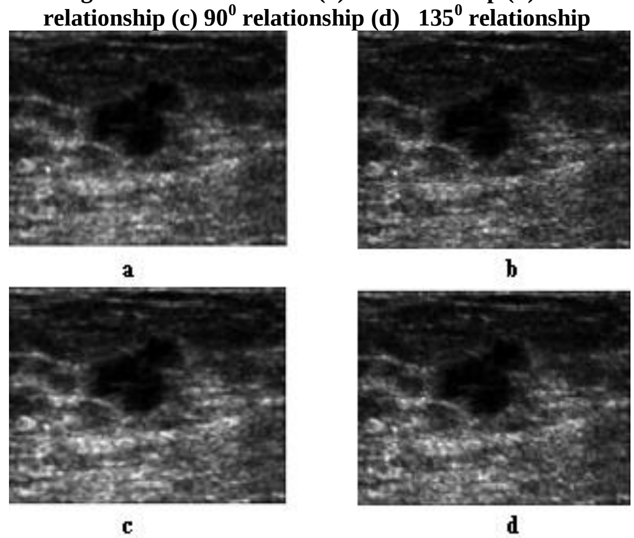

Fig 4: Sum Variance Feature: (a) 0^0 relationship (b) 45^0 relationship (c) 90^0 relationship (d) 135^0 relationship

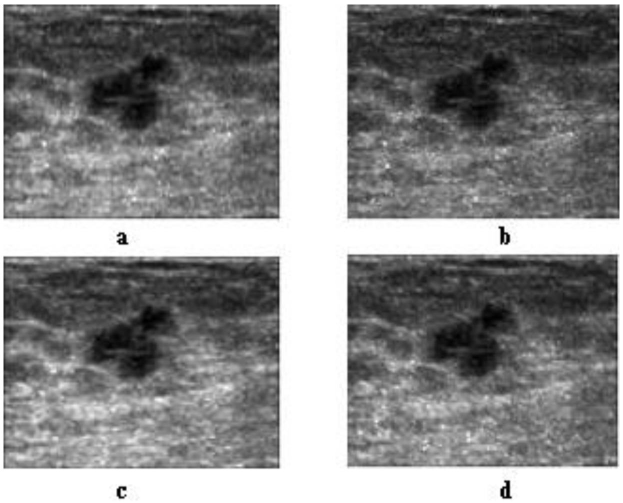

Fig 5: Sum Average Feature: (a) 0^0 relationship (b) 45^0 relationship (c) 90^0 relationship (d) 135^0 relationship

3. LOCAL ADAPTIVE THRESHOLDING

Threshlding technique has a tremendous potential to discriminate between objects (area of interest) and background in a given image. It is widely used tool for image segmentation, due to its responsive properties, simplicity of implementation and computational speed. Thresholding can be categories as bi-level and multilevel [13]. In bi-level, only one threshold has been used to discriminate between object and background gray levels. In multilevel, multiple thresholds are used and gray levels are grouped accordingly. Global thresholding works well when there is clear valley between the modes of histogram related to object and background. N.Otsu's [14] method is based on the computation performed on the histogram of an image. It gives the optimum global threshold, which is used to maximize the inter class variance and obtained the well separated classes in terms of their intensity values. It gives poor performance (over segmentation) for images where bad illumination and random distribution (texture) of gray levels is present. It is indeed a challenge to segment such images using thresholding techniques [15], [16]. Local adaptive thresholding is the solution for such kind of images [17]. We have implemented and tested Otsu threshold on all feature images for 0^0 relationship and superimpose segmentation result is shown in Fig.6.

In this section, local adaptive thresholding technique has been used on feature ultrasound images, which are acquired in the first phase. To implement the adaptive thresholding, feature image needs to be divided into sub-images. Selection of the optimum number of sub-images is specific to content of US image. Therefore selection of number of sub-images involves a trade-off between removal of normal tissue region and retaining edge and tissues of abnormal region in an image. In this paper we are dividing feature image in to 9 sub-images (3 rows and 3 colums). Following algorithm is applied on all feature images with all angular relationship and results are obtained. Superimpose segmentation results for all feature images are shown in Fig.7, Fig.8, Fig.9 and Fig.10.

Thresholding Algorithm:

1. Divide feature image into finite set of sub-images
$$S = \{S_1, S_2, \cdots\cdots, S_A\}, \quad A = a^2,$$
$$where \quad a = \{1, 2, 3, \cdots, z\},$$
$$z \text{ is non negative number}$$
2. Select an initial threshold T_i randomly for the sub-image S_i $\quad where \quad i = \{1, 2, 3, \cdots, A\}$
3. Divide the gray levels of sub-image S_i using T_i in to two groups, G_1 *and* G_2 :
$$S_i(x,y) = \begin{cases} G_1 & if \quad S_i(x,y) \geq T_i \\ G_2 & if \quad S_i(x,y) < T_i \end{cases}$$
4. Compute the average (mean) intensity values $m1$ and $m2$ for the gray levels in G_1 and G_2 respectively
5. Compute new threshold value:
$$T_i = \frac{m1 + m2}{2}$$
6. Repeat step 3 through 5 until the difference between values of T_i in successive iteration is smaller than predefined parameter ΔT_i
7. Apply threshold T_i on sub-image S_i :
$$S_i(x,y) = \begin{cases} 1 & if \quad S_i(x,y) \geq T_i \\ 0 & if \quad S_i(x,y) < T_i \end{cases}$$
8. Repeat step 2 through 7 for complete set S
9. If any sub-image S_i is not threshold properly then repeat step 1 through 8 on only image S_i

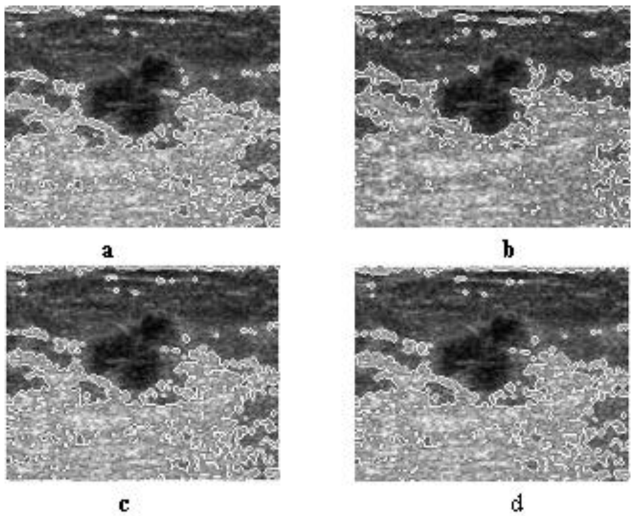

Fig 6: Global thresholding using Otsu's threshold for 0^0 relationship (a) Correlation (b) Sum average, (c) Variance (d) Sum variance

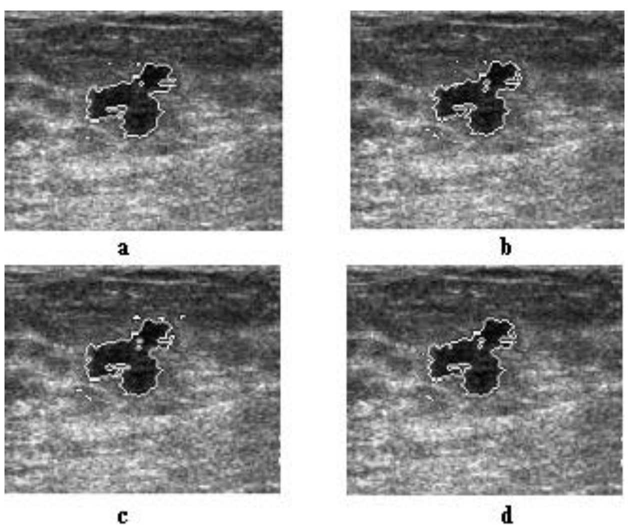

Fig 7: Correlation: (a) 0^0 relationship, (b) 45^0 relationship, (c) 90^0 relationship (d) 135^0 relationship

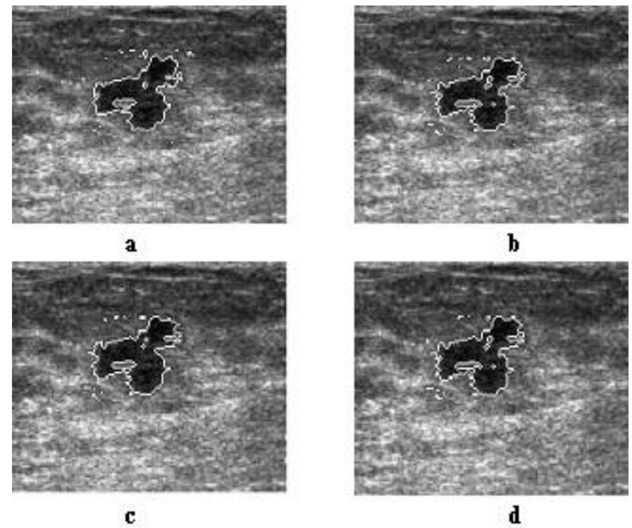

Fig 8: Variance: (a) 0^0 relationship, (b) 45^0 relationship, (c) 90^0 relationship (d) 135^0 relationship

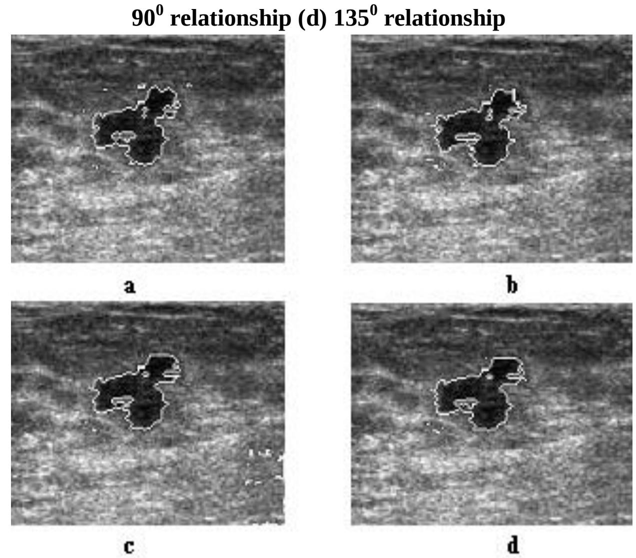

Fig 9: Sum Variance: (a) 0^0 relationship, (b) 45^0 relationship, (c) 90^0 relationship (d) 135^0 relationship

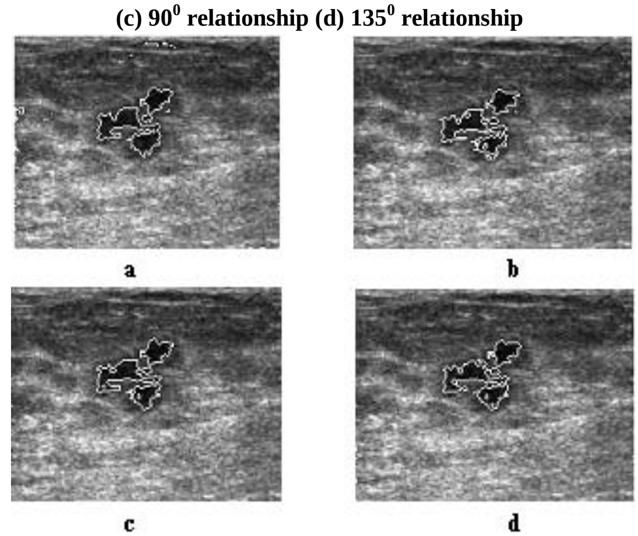

Fig 10: Sum Average: (a) 0^0 relationship, (b) 45^0 relationship, (c) 90^0 relationship (d) 135^0 relationship

4. CONCLUSION
In this paper, we have presented two stage segmentation method applied to the US image for breast cancer detection. In the proposed method, first, Haralick's texture feature are used to characterized and distinguish between breast lesions and normal tissue region. It also makes the edge prominent between normal and abnormal tissue region. Then, adaptive thresholding draws the boundary between the same and gives the proper segmented image. We perform experimentation using GLCM and texture features on US image. In acquired feature images, the boundary gray levels, which are slightly brighter, are merged with the darker gray levels of the defected region. Over segmentation is the problem with Otsu global thresholding, when it applied to these feature images shown in Fig 6. The recursive local adaptive thresholding, shown in Fig 7,8,9 and 10 gives good results and also easy to implement (less complex) as compared to Otsu thresholding. To select appropriate threshold T the value of ΔT in local adaptive thresholding is zero in ideal case, but it would be computationally inefficient, therefore we are using value closer to zero (i.e. ΔT =0.0001). According to the medical experts the result of the Correlation, Variance and Sum variance features is almost similar except Sum average feature.

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