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Research Paper

Feature Extraction and Analysis of Breast Lesion in Ultrasound B Mode and Elastography

S.Sasikala
Assoc.Prof
ECE Dept, Kumaraguru
College of Technology, India

B.Kirthika, P.Malathi
PG SCHOLAR
ECE Dept, Kumaraguru
College of Technology, India

Abstract: Elastography is a non-invasive method in which stiffness of soft tissues are used to detect and classify tumours. The ultrasound B mode and elastographic images were preprocessed and automatic thresholding is done which results in binary images. Segmentation is done by using level set method. The B mode features, elasticity features are computed. The texture features and strain and shape features are calculated for echographic elastographic and the combined image. Classification of above features using neural network is under implementation.

Index terms Bmode,Elastography,elasticity,texture

I.   INTRODUCTION

Non-invasive methods used to diagnose breast cancer still have some disadvantages. Detection techniques are currently based primarily on physical examination, mammography and sonography. Mammography and sonography are currently the most sensitive non-invasive modalities for detecting breast cancer. Ultrasonography is chosen as the work up tool. Ultrasound has long been used to distinguish between harmless, fluid-filled cysts and solid masses. However, solid masses are not always malignant. For example, both fibroadenomas and scirrhous carcinomas are solid and stiff, but only the latter are malignant. The sonographic features for benign and malignant lesions have been shown to override each other substantially (Stavros et al., 1995). In mammography, the compression of breast tissue and the repositioning of the breast for different views cause patient discomfort. It is also difficult to image dense breast tissue in mammography. These limitations of mammography and sonography and the need, not to miss a malignant lesion in the early stage of disease leads to invasive surgical biopsy that cause unnecessary patient discomfort, anxiety and hospitalization in addition to increasing costs to the patient. This substantial problem remains in breast cancer diagnosis.

Benign lesions usually appear smaller or of the same size on sonograms as well as on elastograms. In case of malignant lesions, the size appears larger on the elastogram (Elisa et al., 2000). Unlike benign lesions that have smoother borders and are more loosely bound to the adjacent perilesional tissue, thereby being more mobile, malignant tumors are known to form stellate boundaries that become firmly bound to the surrounding tissue through infiltration. In present study, ultrasound images of the breast, namely the B mode ultrasonogram and elastogram are preprocessed by a Speckle Reducing Anisotropic Diffusion filter (Yu and Acton, 2002). An automatic threshold applied to the preprocessed images results in binary images. The lesion region is identified by Renbo Xia's method of contour evolution. Three sets of features namely texture, strain and shape features are computed from the segmented lesions of both image types.

II.   MATERIALS AND METHODS

IMAGE ACQUISITION:

Initially B mode image of the lesion is taken, following which a slight compression is applied. The effect of breathing and heart beat produce the required compression. The elastogram is generated by the machine by comparing pre and post compressed RF signals and the elastogram is displayed adjacent to the B mode image. The ultrasonograms and elastograms generated are gray scale images.

III.   SEGMENTING THE LESION:

Due to noise and speckles in the ultrasound B mode and elastographic images, noise filtering and edge-enhancement are required. There are several fundamental requirements of noise filtering methods for medical images. One, it should not lose the important information of object boundaries and detailed structures. Two, it should efficiently remove noise in the homogeneous regions and finally, it should enhance morphological definition by sharpening discontinuities. The Speckle Reducing Anisotropic Diffusion (SRAD) filter (Yongjian Yu and T. Scott Acton, 2002) meets these requirements of noise filters and also improves the image quality significantly while preserving the important boundary information and hence, in present study, speckle reducing anisotropic diffusion filtering of real elastography and ultrasound B mode images is done to reduce noise and speckles. Segmentation is required to separate the tumor region from its background. Segmentation algorithms for grey scale images are based on one of the two basic properties

of image intensity values: discontinuity and similarity. In the first category, the approach is to partition the image based on abrupt changes in the intensity, such as edges in an image. The principal approaches in the second category are based on partitioning an image into two regions that are similar according to a set of predefined criteria. In present study, automatic threshold and level set active contour method, based on the above criteria are used for segmentation.

In an elastogram, the tumor region appears to be darker and the background bright. In present study, the preprocessed images are subjected to the above mentioned automatic threshold scheme, resulting in binary images as this aids in separating the lesion from its background. The area of lesion is segmented from the binary image by applying level set segmentation technique.

IV. LEVEL SET METHOD:

Level sets are first described by Osher and Sethian (1988) as a method for capturing moving fronts. In the level set formulation, the segmentation problem is equivalent to the computation of a surface Γ (t) that propagates in time along its normal direction. The Γ surface is also called a propagating front, which, according to Osher and Sethian (1988), is embedded as a zero level of a time- varying higher dimensional function (x, t):

$$\Gamma(t) = \{x \in \Re^3 | \phi(x,t) = 0\}$$

An evolution equation for an interface Γ, where Γ is a closed curve can be written in a general form:

$$\frac{\partial \phi}{\partial t} + F |\Lambda \phi| = 0$$

The function describes the curve by

$$\phi(x, t) = d$$

where, d is a signed distance between x and the surface Γ. If x is inside (resp. outside) of Γ, then d is negative (resp. positive). The function F is a scalar speed function that depends on image data and the function. The main drawback of this procedure is that during the evolution, can assume sharp or flat shapes. To overcome this problem, is initialized as a signed distance function before the evolution.

In present study, variational level sets are used, which are more robust than those originally proposed by Osher and Sethian because they incorporate shape and region information into the level set energy functions. Here, the initial contours of lesions of both ultrasound and elastography images are determined by the method proposed by Xia and Liu (2007). This algorithm consists of finding all endpoints in an edge map.

V. FEATURE EXTRACTION

They are extracted from the segmented lesion to identify whether it is cystic, beningn, malignant .

Strain and shape features:

The malignant tumor size is larger is elasticity images than in the B mode image based on the difference in the lesion size in B mode and elasticity images it is considered to calculate the features namely area difference, perimeter difference and contour difference

Area difference

The area difference is defined as difference between the area lesions of ultrasound B mode and elastographic image. The area difference used to compare area the images as area changes according to applied pressure.

$$\text{Area difference} = \frac{a_u - a_e}{a_u} \times 100$$

Where au, ae are lesions of ultrasound and elastogram images.

Perimeter difference

The perimeter difference is calculated by distance between each adjoining pairs of pixels around the lesions.it is length of the nuclear envelope calculated length of a polygonal approximation of the boundary (B), where p is perimeter of lesion. Polygonal approximation is approximating a closed curve as a 2D polygon by which a simple representation of the planar object boundary is provided,

$$p = \sum_{x \in B} 1$$

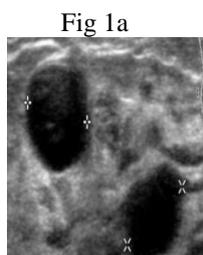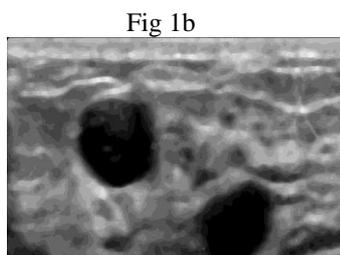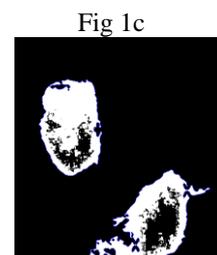Fig 1a   Fig 1b   Fig 1c

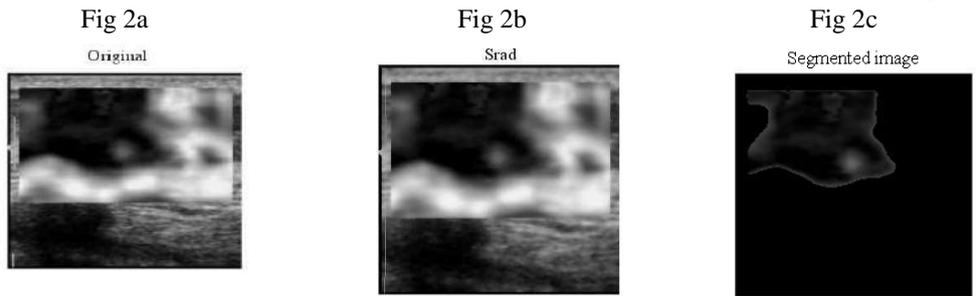Fig. 1a: Original US B mode image of malignant lesion   Fig. 1b: Filtered image Fig. 1c: Segmented tumor   (ROI)

Fig 2a   Fig 2b   Fig 2c

Fig. 2a: Original elastogram of malignant lesion Fig. 2b: Filtered image Fig. 2c: Segmented tumor (ROI)

Fig 3a   Fig 3b   fig 3c
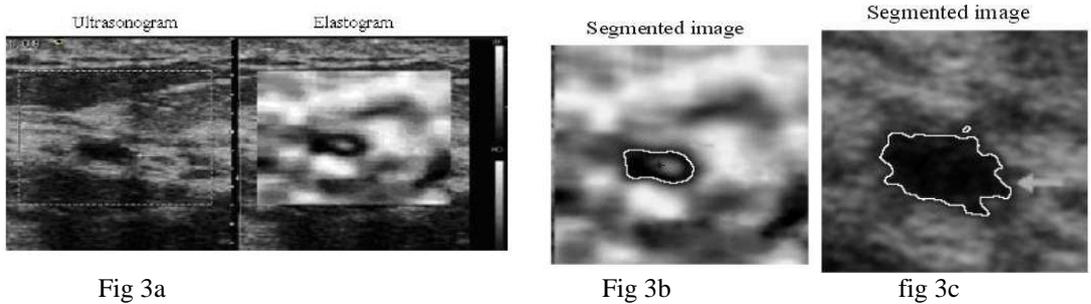
Fig. 3a: Ultrasound image and elastogram of a cystic lesion Fig. 3b: Computer delineated margin of lesion of Ultrasound image a sound image Fig. 3c: Computer delineated margin of lesion of elastogram

Solidity

Shape values can be used to distinguish between benign and malignant tumors. Benign lesions usually have smooth shapes and so they produce a regular shape in both ultrasound and elastographic images whereas malignant lesions present irregular shapes in elastograms. This difference can be obtained in terms of a feature called solidity:

$$Solidity = \frac{cvx_{ar}}{\sum \frac{cvx_{ar} - tumor_{ar}}{N_{tot}}}$$

Where,
Ntot = The total number of imaging modalities involved
cvxar = The area obtained from the convex hull of a tumor
tumor ar = The area of tumor.

Contour difference:

The contour difference feature is used to compare differences of contours between the Ultrasound B mode lesion and elastogram lesion. Initially the contours are registered by linear conformal Method transformation. It is the transformation of an image by scaling the image, rotating the image and translating the image to a different coordinate system. Intensity weighted centroids are used as reference points for the two lesions (Moon and Chang, 2005):

$$Contour \ difference = \frac{N_{condiff}}{N} \times 100$$

Where:
Ncondif = The pixel difference between the two registered contours
N = The number of tumor pixels in the ultrasound image .

Width to height difference:

Due to applied stress, a benign lesion appears smaller in an elastogram compared to B-scan image, whereas a malignant lesion appears larger in an elastogram because of its solid nature. Based on this, the width to height difference can be taken as a feature. An ellipse that has same normalized second central moment as the region of interest is drawn. The major axis length (height) and minor axis length (width) of the ellipse a0re computed. The ratio of width to height is calculated for lesions of ultrasonogram and elastogram respectively.

Texture features:

The texture features represent changes of grey level intensity. The second orderstatistical features namely standard deviation, energy, entropy, dissimilarity, homogeneity and contrast arecomputed using Grey level Co-

occurrence Matrix (Haralick et al., 2007) from ultrasonogram andelastogram. This square matrix estimates the inter-pixel positioning and each cell carries the count of thenumber of times a pixel pair occurs as a function of two other parameters, the distance 'd' and the angle 'q'between them. Generally the value of 'd' is fixed at 1.The minimum and maximum value of each feature is shown in Table 1-3. The obtained features are presented in Table 1-3.

Table 1: Texture features of ultrasonogram

| Features | (Minimum to maximum) | | |
	Benign lesion	Malignant tumor	Cystic lesion
Energy	10000-50000	500-10000	7000-43000
Entropy	-830 to -1290	-120 to -280	-2000 to -16000
Dissimilarity	100-500	40-10000	3000-15000
Homogeneity	30-430	57 -78	300-2000
Contrast	100 to1000	150-3000	450-20000
SD	20-60	0.22 -1.0	0.6-35

Table 2: Texture features of elastogram

| Features | (Minimum to maximum) | | |
	Benign lesion	Malignant tumor	Cystic lesion
Energy	300-1000	2000-8000	3000-20000
Entropy	-60 to -540	-300 to -500	- 780 to -8000
Dissimilarity	3000-4000	80-1200	1300-20000
Homogeneity	52-278	268-530	160-1000
Contrast	100 to1000	90-2500	430-3000
SD	0.1-0.25	0.7-40	0.39-0.84

Table 3: Strain and shape features from ultrasongram and elastogram

| Features | (Minimum to maximum) | |
	Benign and cystic lesion	Malignant tumor
Area difference	5-100	-60 to -10000
Solidity	0.6-0.8	0.2-0.6
Perimeter difference	10-100	100-1000
Contour difference	7-100	1-10
Width-height ratio	-40 to -150	15-100

VI. RESULTS

The segmentation results are shown in Fig. 1-4. Figure 1a-f show the various stages of filtering and segmentation of an US B mode image of a malignant lesion. Figure 2a-f show the various stages of filtering and segmentation of an elastogram of a malignant lesion. Figure 3a-c shows the ultrasound image and elastogram of a benign lesion and their segmented images. Figure 4a-c shows the ultrasound image and elastogram of a cystic lesion and their segmented images. The computed delineated margin is the white outline. The features extracted are listed in Table 1-3. Table 1 presents the texture features of malignant, benign and cystic lesions of an US B mode image. Table 2 presents the texture features of malignant, benign and cystic lesions of an elastogram. Table 3 presents the strain and shape features obtained from parameters of both US and elastography images. Malignant masses are stiffer and therefore deform less than benign masses, besides they appear darker and arger than benign masses on an elastogram. A benign tumor would be of comparable size in both sonogram and elastogram. A cyst is characterized by its inner anechogenic substance and thin echogenic outer wall nature. It is depicted as nidus (bull's eye appearance) in an elastogram (Fig 4c). The computed delineated margin is the white outline.

From Table 3, it is observed that strain and shape features extracted using parameters from US B mode image and elastogram, well differentiate the malignant tumors from benign and cystic lesions. Hence ,elastogram texture features are superior in differentiating cystic lesions from benign conditions. The strain and shape features well differentiate the benign from malignant lesions. Hence, we conclude that it is appropriate to combine the information obtained from both US elastography and US B mode images for better diagnosis.

VII. CONCLUSION

In this proposed method the two sets of images are initially preprocessed by filtering and then by an automatic threshold technique. The level set method is utilized to segment the lesion in the combined image. The texture, strain and shape features are calculated from the segmented breast lesions. Some of the features are distinct in an elastogram for the three given conditions and therefore elastogram increases the specificity of diagnosis. Classification of breast lesions using strain and texture features obtained from ultrasound images and elastograms is under implementation.

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