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Segmentation of Breast Lesions in Ultrasound Images Using Spatial Fuzzy Clustering and Structure Tensors

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Abstract—Segmentation in ultrasound images is challenging due to the interference from speckle noise and fuzziness of boundaries. In this paper, a segmentation scheme using fuzzy c-means (FCM) clustering incorporating both intensity and texture information of images is proposed to extract breast lesions in ultrasound images. Firstly, the nonlinear structure tensor, which can facilitate to refine the edges detected by intensity, is used to extract speckle texture. And then, a spatial FCM clustering is applied on the image feature space for segmentation. In the experiments with simulated and clinical ultrasound images, the spatial FCM clustering with both intensity and texture information gets more accurate results than the conventional FCM or spatial FCM without texture information.

Keywords—fuzzy c-means, spatial information, structure tensor, ultrasound image segmentation

I. Introduction

BREAST cancer is the most common form of cancer and the second cause of cancer deaths among women. Mammography is an effective method for breast cancer diagnosis but it has a low negative predictive value, which leads to more needless breast biopsies so it is necessary to use some other ways to ameliorate the result. Breast ultrasound can be used to distinguish benign breast lesions from malignant ones and detect breast lesions invisible on mammography. It is also recommended as the primary imaging technique for women younger than thirty with breast problems. So ultrasound has been employed as an adjunct to mammography. The morphology [1] and texture features between benign and malignant tumors in an ultrasound image are important indications for classifying breast tumors. The segmentation of breast ultrasound image performs as an important antecedent step for advanced medical application, such as computer-aided diagnosis (CAD). However, segmentation of ultrasound images is quite challenging due to the interference from speckle noise and fuzziness of boundaries. A high failure rate of analyzing image lesions appears [2] because the computerized segmentation failed.

In ultrasound imaging, the speckle noise which gives a granular appearance makes segmentation complicated. The general idea is to do noise reduction before segmentation for preprocessing. However, the big-size speckles and the repeated speckle structure have a much greater effect to image quality than the normal noise such as Gaussian noise. Thus some methods treated the ultrasound images as textured images. To deal with textured images, texture feature extraction is used for preprocessing instead of noise reduction. Many different approaches have been employed in the literature for texture feature extraction based on Laws texture feature, multiple resolution techniques, Markov Random Fields, Gabor filters and so on. There are still some well-established texture feature extraction methods rarely used in ultrasound images, such as structure tensors (second moment matrix) [3].

Fuzzy c-means (FCM) clustering [4] is an unsupervised technique that has been successfully applied in classifier designs for image segmentation. Pixels with similar features in an image can be classified into the same cluster. The advantages of FCM include a straightforward implementation and applicability to multichannel data make. Especially, the ability of FCM to model uncertainty within the data give a solution to deal with the fuzziness of the boundaries in ultrasound images. A major disadvantage of conventional FCM is that pixels are regarded isolated with their positions. Obviously, this does not cohere with the spatial characteristic of an image. Pham [5] modified the objective function of the standard FCM by adding a spatial penalty term. Liew et al. [6] ameliorates the dissimilarity measure between data and the cluster prototype by making it be a weighted sum of the classified pixel and its neighborhoods. The modified FCM algorithm improved the results of conventional FCM method on noisy images. However, the way in which they incorporate the neighboring information limits their application to single-feature inputs.

Fig. 1 shows the framework of the proposed method which use spatial FCM by improving the membership function and utilizes both the image intensity and speckle pattern extracted from image texture. The following section starts with a brief introduction of the linear structure tensor and nonlinear structure tensor. In section 3, the spatial FCM is used in tensor domain and an image intensity channel is added into the extracted feature space. Section 4 shows experiment results of simulated data and real ultrasound data. The paper is concluded with a summary in section 5.

II. Structure tensor for speckle feature extraction

The local structure tensor [3] (also called scatter matrix or second moment tensor) provides a representation of image

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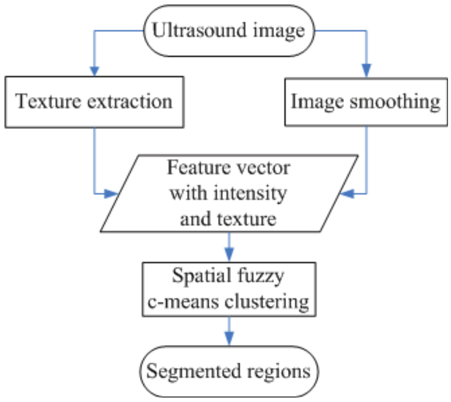

Fig. 1. Framework of the proposed method.

texture by taking into account how the gradient changes within the vicinity of any investigated point. Comparing Gabor filter, it has less parameters and it also provides a controllable scales more easily than wavelet transform. For a scalar image I, the linear structure tensor with a rank of 2 is defined as follows:

$$\begin{aligned} J_\rho &= \begin{pmatrix} J_{11} & J_{12} \\ J_{21} & J_{22} \end{pmatrix} \\ &= K_\rho * (\nabla I \nabla I^T) \\ &= \begin{pmatrix} K_\rho * I_x^2 & K_\rho * I_x I_y \\ K_\rho * I_x I_y & K_\rho * I_y^2 \end{pmatrix} \end{aligned} \tag{1}$$

where K_ρ is a Gaussian kernel with standard deviation ρ , and subscripts of I denote partial derivatives. This is a classical form of structure tensors, which is a symmetric positive semi-definite matrix. Fig. 2 shows the channels in structure tensor which pick up the speckle shape and position of an ultrasound image but throw away the intensity information. This expression of speckle texture facilitates to refine the edge that extracted from the original image. Gaussian convolution in (1) not only smoothes the noise, but also provides a scale-space with the integration scale ρ which controls the smoothness of edges by apply segmentation in different scales.

The Gaussian filter implies a process of linear isotropic diffusion which has a problem that it blurs edges at the same time of smoothing. Thus, Perona and malik [7] proposed the following nonlinear diffusion PDE to preserve edges:

$$\partial_t u = div(g(|\nabla u|^2)\nabla u) \tag{2}$$

where ∇ is the gradient operator, div the divergence operator, $|\cdot|$ denotes the magnitude. The initial condition, $u(t=0)$, is equal to original image I. $g(\cdot)$is the diffusivity function, which is proposed in [7] to be

$$g(s^2) = \frac{1}{1+\frac{s^2}{k^2}} \tag{3}$$

or

$$g(s^2) = \exp(-\frac{s^2}{k^2}) \tag{4}$$

where k is an edge magnitude parameter.

In [8] , the Perona-Malik filter was regarded as an isotropic model, since it utilizes a scalar-valued diffusivity and not a

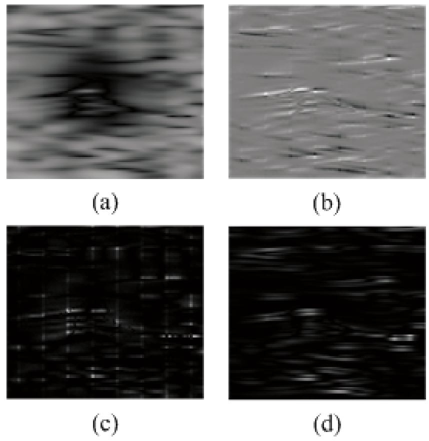

Fig. 2. (a) Original ultrasound high-reflection image I. (b) (c) (d) Channels of $I_x I_y$, I_x^2 and I_y^2 in structure tensor respectively

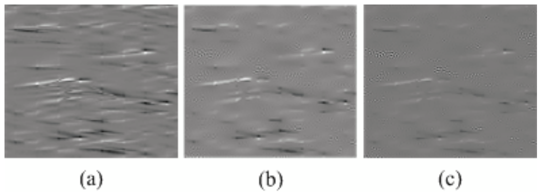

Fig. 3. $I_x I_y$ in nonlinear structure tensor ($k=5$). (a) $t=0$. (b) $t=7$. (c) $t=8$.

diffusion tensor. In the case of anisotropic, the smoothing is adapted not only to the locations of pixels but also different directions and it allows smoothing along image edges while inhibiting smoothing across edges. For matrix-valued data, the anisotropic nonlinear diffusion can be express as

$$\partial_t u_{ij} = div(g(\sum_{k,j=1}^{n} \nabla u_{kl} \nabla u_{kl}^T)\nabla u_{ij}) \quad (i,j=1,\cdots,n) \tag{5}$$

where u_{kl} is a tensor channel. Fig. 3 shows the texture of $I_x I_y$ defined by (5) in different scales. As the diffusion time increases, the contrast of texture becomes lower, which will exert a weaker influence on the segmentation. This approach is generalized directly from the vector-valued anisotropic diffusion, which means the spatial structure of tensors is ignored.

III. Segmentation method

A. Spatial FCM

FCM [4] is an iterative clustering algorithm with the characteristic that it allows feature vectors to belong to multiple clusters and the belongingness is described by the grade of membership. Let $X=(x_1,x_2,\cdots,x_N)$ denotes an image with N pixels to be partitioned into C clusters. The conventional algorithm is based on minimization of the following objective function:

$$J_m = \sum_{i=1}^{N}\sum_{j=1}^{C} u_{ij}^m \|x_i - c_j\|^2 \tag{6}$$

where u_{ij} is the membership function of x_i in the cluster j, x_i is the ith measured data, c_j is the center of the jth cluster, and $\|\cdot\|$ is any norm expression the dissimilarity between any measured data and the center. The exponent m, called fuzzifier, determines the level of cluster fuzziness. The recommended value of the fuzziness index is 2 because the updated fuzzy membership value is proportional to the square of the inverse distance from a specific segment location to each project's centroid [4]. The membership functions are constrained to be positive and satisfy:

$$\sum_{j=1}^{C} u_{ij} = 1 \tag{7}$$

The membership function is updated by the following:

$$u_{ij} = \frac{1}{\sum_{k=1}^{C} \left(\frac{\|x_i - c_j\|}{\|x_i - c_k\|} \right)^{\frac{2}{m-1}}} \tag{8}$$

And the center is

$$c_j = \frac{\sum_{i=1}^{N} u_{ij}^m x_i}{\sum_{i=1}^{N} u_{ij}^m} \tag{9}$$

One of the important characteristics of an image is that neighboring pixels are highly correlated. This spatial relationship between pixels is important in clustering, but it is not utilized in the conventional FCM algorithm, where the noise leads a misclassification because the noised pixel takes a different feature with the correct one. To reduce the effect of noise, the probability that a noised pixel belongs to the same cluster with its neighbors should become greater. In [9], they proposed a spatial FCM algorithm by altering the membership weighting of each cluster. Referring to this idea of incorporating spatial information, a spatial membership function is defined as:

$$u'_{ij} = \frac{u_{ij}^p f(u_{ij})^q}{\sum_{k=1}^{C} u_{ik}^p f(u_{ik})^q} \tag{10}$$

where p and q are parameters to control the relative importance of u and f terms. $f(u)$ is a spatial weight function which can be defined as a two dimensional average or median filter. In a homogenous region, the spatial weight function simply fortifies the original membership, and the clustering result remains unchanged. However, for a noisy pixel, (10) makes its membership be closed to its neighborhoods. As a result, we can classify the noisy pixel correctly. What should be noted is that the situation where $p = 1$ and $q = 0$ is identical to the conventional FCM.

Some clustering methods estimates the initial cluster prototype to allow a faster segmentation. It is easy for scalar valued data to obtain the cluster prototypes estimation using image histogram or some threshold techniques, but these techniques is not adapted to vector valued data. In [10], they initialized the cluster prototypes by genetic algorithm which need 300 generations for optimization. In some sense, this step increased the total calculation time, so to set the initial memberships randomly is alternative. The spatial FCM algorithm is as follows:

1) Generate random numbers with the range from 0 to 1 to be the initial memberships. Set the number of cluster and calculate c_i using (9). Select a very small positive number ϵ.
2) Compute u_{ij} using (8).
3) Map u_{ij} into the pixel position and calculate the modified membership u'_{ij} using (10). Compute the objective function J.
4)Update center c using (9)
5) Repeat steps from 2) to 4) until the following termination criterion is satisfied:

$$\|J_{new} - J_{old}\| < \varepsilon \tag{11}$$

B. Segmentation in Image Feature Domain

The classical FCM is based on vector-valued data, and we usually use Euclidean norm as the distance measures. To develop a tensor-valued version of FCM, the similarity between tensors should be defined firstly. Alexander et al. [11] discussed different similarity measures for matching of diffusion tensor images and indicated that the Frobenius difference measure of tensors was the best in the context of images registration. The Frobenius distance is defined as:

$$dist(A, B) = \sqrt{\sum_{i=1}^{m} \sum_{j=1}^{n} |a_{ij} - b_{ij}|^2} \tag{12}$$

where a_{ij} and b_{ij} are elements of tensor data A and B with indices i and j. The Frobenius distance of a matrix is identical to the Euclidean distance of a vector in (15). Moreover, the nonlinear diffusion of a tensor does not consider the position of different channels, neither. Therefore, the tensor-valued FCM is equals to the vector-valued one.

The general idea is that the extracted texture ameliorate edges confused speckle noise while he gray level image after smoothed indicates the basic region of target. So the image feature is constructed as:

$$F = [\ J_{11} \quad J_{12} \quad J_{22} \quad I_t\ ] \tag{13}$$

where J_{11}, J_{12} and J_{22} are channels in structure tensor and I_t is the filtered image by anisotropic diffusion with diffusion time t. Because J_{21} is equal to J_{12} in structure tensor J, one is enough for the texture feature. The values of different channels are always not in the same unit, which makes it incommensurable to each other. So the data is normalized by dividing each column by its standard deviation. The feature combined image intensity with texture contains a lot of useful information for the discrimination between different areas. However, the multichannels increase computing time, especially as the image size gets bigger. To overcome this disadvantage, principle components analysis (PCA) is alternative to summarize the data into fewer dimensions.

IV. Experiment results and discussions

To evaluate the performance of the proposed algorithm, both simulated and real breast ultrasound images are used. The simulated data in Fig. 4(a) is acquired from an ultrasound simulation package, "Field II" [12], which provides a framework to simulate ultrasound imaging. There are three simulated cysts, the diameters of which are 4, 5, and 6 mm from top to bottom. The simulated image has not been processed by any noise reduction or contrast enhancement method before segmentation. That is different from real ultrasound images because ultrasound instruments always have an image enhancement module to make a better display.

Fig. 4 displays the results of FCM, spatial FCM with texture information and spatial FCM without texture information. The signal-to-noise ratio (SNR) in Fig. 4(a) is about $14dB$. The number of clusters is 2 and the image is divided into two regions. The intensity images, I_t , in both Fig. 4(c), (d) and (e) are acquired by anisotropic diffusion filters with 15 iterations and $k = 25$. The texture feature is extracted by nonlinear structure tensor with 12 iterations and $k = 5$. m is set to 2 in both conventional and spatial FCM. In spatial FCM, $p = 0$, $q = 1.1$ and A median filter with 7×7 windows is chosen to get the spatial weight for the membership of data.

In Fig. 4, the results of spatial FCM with both intensity and texture information characterize the most accurate boundaries. The spatial FCM with only intensity information in Fig. 4(c) makes more misclassification at the edge and that may cause a wrong characterization of the tissue. The result of conventional FCM in Fig. 4(d) appears a lot of noisy area in both the background and edges. Fig. 4(e) using the spatial FCM with texture and intensity information shows that the texture extracted by structure tensors refines the border of lesion regions and it can cope with the speckle noise. In this experiments, the most sensitive parameters are the iteration number and diffusivity parameter k in nonlinear diffusion of structure tensors. This two parameters control the smoothness of speckle patterns. If the texture is over smoothed, the texture information is not enough to rectify the misclassification by speckle noise. If the texture is too strong, it will corrupt the image as a kind of artifacts. It is important to find a balance between noise reduction and edge representation.

Fig. 5 shows the result of real ultrasound image segmentation. ultrasound image of breast with 180-by-124-pixel is used and a manual delineation of the lesion area is compared with the result. All the parameters of Fig. 5 are the same with that of Fig. 4 except the image intensity which is filtered by anisotropic diffusion with 10 iterations and $k = 5$. The reason is that the real image has already been processed by noise reduction and contrast enhancement before displayed in ultrasound instruments.

Two types of cluster validity functions, partition coefficient V_{pc} and partition entropy V_{pe} [9], are used to evaluate the performance of fuzzy partition. They are defined as follows:

$$V_{pc} = \frac{\sum_j^N \sum_i^C u_{ij}^2}{N} \tag{14}$$

and

$$V_{pe} = \frac{-\sum_j^N \sum_i^C [u_{ij} \log u_{ij}]}{N} \tag{15}$$

The idea of these validity functions is that the partition with less fuzziness means better performance. As a result, the best clustering is achieved when the value V_{pc} is maximal or V_{pe} is minimal. Table I indicates that the proposed FCM methods perform better than the conventional FCM, and the spatial weighted function with median filter is a little better than that with average filter.

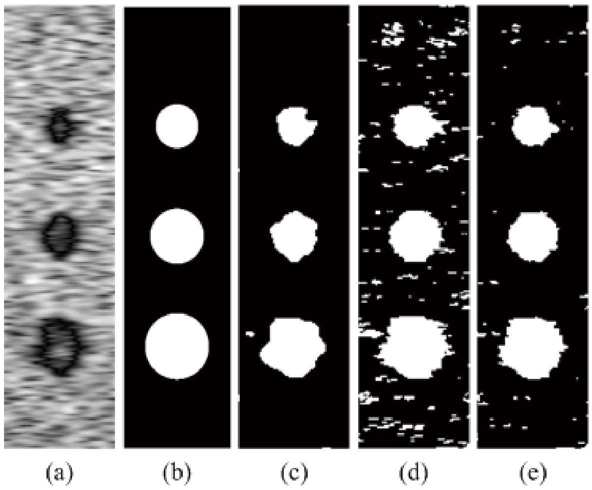

Fig. 4. (a) Original images. (b) Ideal regions (c) Spatial FCM with only intensity (d). FCM with texture and intensity feature. (e) Spatial FCM with texture and intensity information.

TABLE I
EVALUATIONS OF CLUSTERING

	SFCM/Average	SFCM/Median	FCM
V_{pc}	0.8112	0.8116	0.7381
V_{pe}	0.3077	0.3068	0.4120

Two factors are imported to evaluate the segmentation method and the three cyst regions are measured respectively. The area error is defined as the result of the sum of the total number of pixels in the cyst divided by the sum of number of misclassified pixels. Because the original shape of the cysts is an ideal circle, the shape of segmented region is measured with form factor calculated by

$$F = \frac{\|P\|^2}{4\pi A} \tag{16}$$

where P is the perimeter and A is the area of the segmented region. F is a positive number that is always bigger than one unless the area is a circle which makes F equal to one. Thus, the form factor indicates the deviation of the shape from a circle. Table II shows the measurement of the segmented regions using three fuzzy clustering methods, where I and T refer to the intensity and texture feature applied to images, SFCM refers to the proposed spatial FCM and FCM refers to the conventional method. The area errors of SFCM/I is the biggest because speckle noise distort the image so much that intensities cannot represent the edges accurately. SFCM/I&T is comparable to FCM/I&T in terms of area error, but the form factor of FCM/I&T is much bigger which is caused by the rough borders of the segmented region. This kind of roughness may bring about the misdiagnosis of cancer because the roughness of borders is one of the critical indicators in breast ultrasound images.

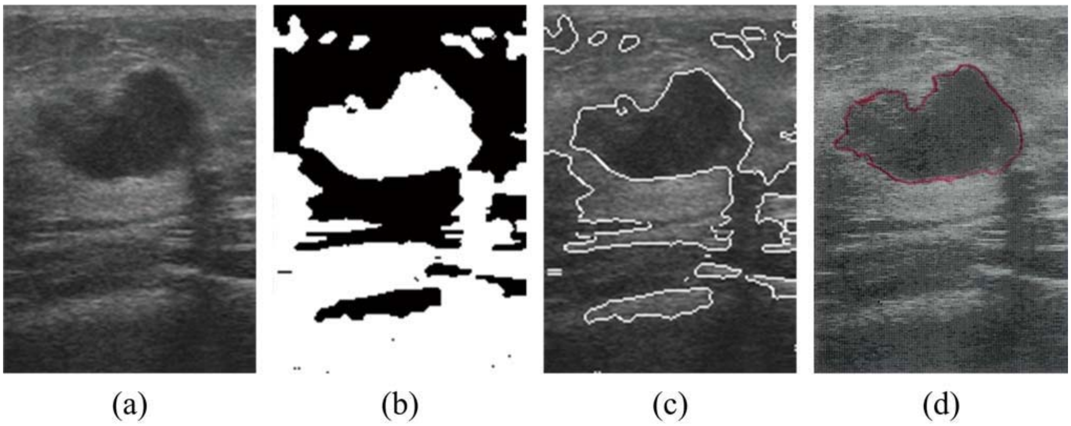

Fig. 5. (a) An original breast ultrasound image. (b) The result of proposed method with 2 clusters, (c) Edge detection of (b) by the sobel mask, (d) The lesion delineated by the doctor.

TABLE II
EVALUATIONS OF SEGMENTED REGIONS

	Area Error			Form Factor		
Method	4mm	5mm	6mm	4mm	5mm	6mm
SFCM/I&T	0.2108	0.2333	0.1610	10.74	9.969	11.05
SFCM/I	0.2836	0.3002	0.1932	11.69	11.78	11.51
FCM/I&T	0.2780	0.1543	0.0784	20.33	12.52	16.46

V. CONCLUSION

In this study, an effective segmentation method is presented to extract lesion regions in ultrasound breast images on the simulated and clinical images. Both texture and intensity information are utilized to get an accurate result. The texture extracted by nonlinear structure tensors with different scales can be used to get the balance between noise reduction and edge representation. The proposed spatial FCM is more tolerant to noise than the conventional one. Based on the speckle texture and image intensity, it copes with the speckle noise and fuzziness of boundaries in ultrasound images.

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