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SEGMENTATION OF ULTRASONIC IMAGES USING FUZZY SETS

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Abstract

An image segmentation technique based on fuzzy sets for ultrasonic B-scans is presented. The fuzzy c-means algorithm is adapted to B-scan images. The classes constituting a region are obtained through fuzzy partitioning based on local statistics information. The performance of the method is tested on phantom and tissue images and the results are presented.

1. Introduction

In medical imaging, coherent nature of phase array systems results in speckle spots that degrade the image quality. Speckle decreases the observers' ability in diagnostic examination and the efficiency of further image processing. Additionally, organ boundaries, randomly distributed tissue structures and boundaries between different tissues are ill-defined on B-scan ultrasonic images.
For simple and reliable diagnostic examination, image enhancement, smoothing [1], and segmentation [2, 3, 4, 5] have been involved in medical applications.

The ill-defined structure of ultrasonic images allows to separate regions with a fuzzy set theoretic image segmentation method. The feature vectors belong to the same classes are clustered together in the feature space, whereas the other feature vectors lie farther apart from each other. In this study, the fuzzy c-means algorithm (FCM) is used to partition the feature space.

To test the segmentation method, a phantom image and a clinical liver image are digitally processed. The phantom image is produced from a *3.3* MHz, *64* element array system whereas the clinical liver image is obtained from a commercial phased array scanner.

2. The Fuzzy C-means Clustering Algorithm

The fuzzy c-means algorithm (also called fuzzy ISODATA) has been developed by Dunn [6]. The algorithm uses an iterative optimization of an objective function based on a weighted similarity measure between the pixels in the image and each of the c-cluster centers. A local extremum of this objective function indicates an optimal clustering of the input data. The objective function to be minimized is given by

$$J_m(U,v)=\sum_{k=1}^{n}\sum_{i=1}^{N_c}(u_{ik})^m(d_{ik})^2\|x_k-v_i\|^2$$

where u_{ik} is the fuzzy membership value of the k th pixel in the i th cluster, d_{ik} is any inner product induced norm metric. In contrast to hard clustering, the fuzzy membership value ranges from 0 to 1. The larger values of m means fuzzier clustering, while $m=1$ corresponds to a hard clustering. The v is the set of c-cluster centers which are treated as vectors, and U is the fuzzy c-partition of the image.

It has been shown in [7] that for m greater than one, under the assumption that $x_k \neq v_i$ $\forall i, k$, $(\overline{U},\overline{v})$ may be a local minimum of J_m only if

$$\overline{u}_{ik}=\left(\sum_{j=1}^{N_c}\left(\|x_k-\overline{v}_i\|/\|x_k-\overline{v}_j\|\right)^{2/(m-1)}\right)^{-1}, \qquad \forall i, k, \tag{1}$$

and

$$\overline{v}_i=\left(\sum_{k=1}^{n}(\overline{u}_{ik})^m.x_k\right)/\left(\sum_{k=1}^{n}(\overline{u}_{ik})^m\right), \qquad \forall i. \tag{2}$$

The FCM algorithm can be outlined as:

Step 1. Fix c, $2\leq N_c\leq n$. Select any inner product metric norm for R^d ($X=\{x_1, x_2,\ldots,x_n\}$ is a finite data set in R^d; $x_k \in R^d$, $1\leq k\leq n$), fix m, $1\leq m\leq\infty$, initialize $\overline{U}^{(0)} \in M_{fc}$, and $p=1$,

Step 2. Calculate fuzzy cluster centers $\{\overline{v}^{(p)}\}$ using $\overline{U}^{(p-1)}$ and the condition specified in Equation 2,

Step 3. Update $\overline{U}^{(p)}$ using $\overline{v}^{(p)}$ and the condition specified in Equation 1,

Step 4. Compare $\overline{U}^{(p)}$ with $\overline{U}^{(p-1)}$ in a convenient matrix norm: If $\|\overline{U}^{(p)}-\overline{U}^{(p-1)}\|\leq\varepsilon$, then terminate, else set $p\leftarrow p+1$ and return to Step 2.

In this study, the inner product induced norm metric is chosen as the Euclidean norm for J_m because of its simplicity, and $m=2$. In addition to the m parameter, the number of cluster centers, N_c, the convergence threshold, ε, the initial partition of membership values, $\overline{U}^{(0)}$, and the number of items, n, must be properly chosen.

In this study, each pixel of the image is presented as a vector in feature space. The features used in fuzzy c-means algorithm of each pixel are gray level, local statistics, and the pixel location. The measurement of variance vs mean is used to examine the speckle statistics on a phantom image and a liver image. For this measurement, window size is selected as *9x9* pixels. The means and variance are computed as follows:

$$\mu_{i,k} = 1/K^2 \sum_{m=-K/2}^{K/2} \sum_{n=-K/2}^{K/2} x_{i-m,j-n} \qquad (3)$$

$$\sigma_{i,j}^{\ 2} = 1/K^2 \sum_{m=-K/2}^{K/2} \sum_{n=-K/2}^{K/2} (x_{i-m,j-n} - \mu_{i,j})^2 \qquad (4)$$

$x_{i,j}$ is the pixel at the location (i, j) and KxK is the window size. The ratio of variance to mean is evaluated for each pixel. Further details about this measurement and choice a proper window size can be found in [1].

3. Segmentation of B-scan Images

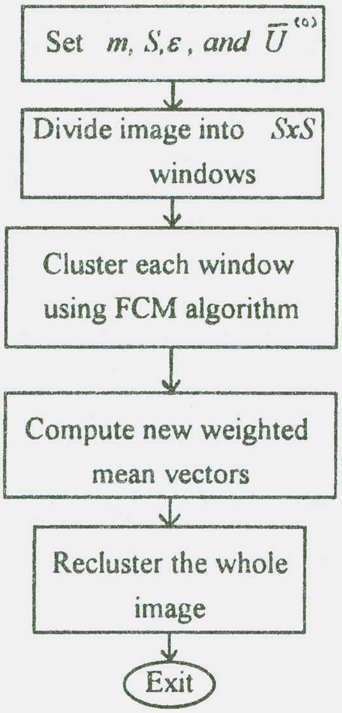


Figure 1. Block diagram of the segmentation procedure.

For evaluation of fuzzy partitioning based segmentation, a phantom image *200x200* pixels in size and a liver image *216x216* in size were used. The procedure consist of two steps. In the first step, the image is divided into small portions, each has a size of *SxS*. Processing of each window pixels are clustered using $m=2$, the number of the cluster centers N_c which is set initially, and the identical initial matrix. Also the convergence threshold, ε , is selected as *0.03*. In this step of the segmentation procedure, the number of cluster centers on a whole image ranges from N_c to WxN_c, where W is the number of image portions. In the second step of the procedure, the image is segmented in N_c regions using the weighted mean vectors calculated for each window in the first step. To recluster the pixels, the local statistics and the gray level of the pixels are selected to compute the distance. In this part, the new weighted mean vectors are calculated using a simple scheme: for example, for $N_c=3$, the cluster centers are calculated as maximum, minimum and average values of the weighted mean vectors with Euclidean distance norm.

4. Experimental Results

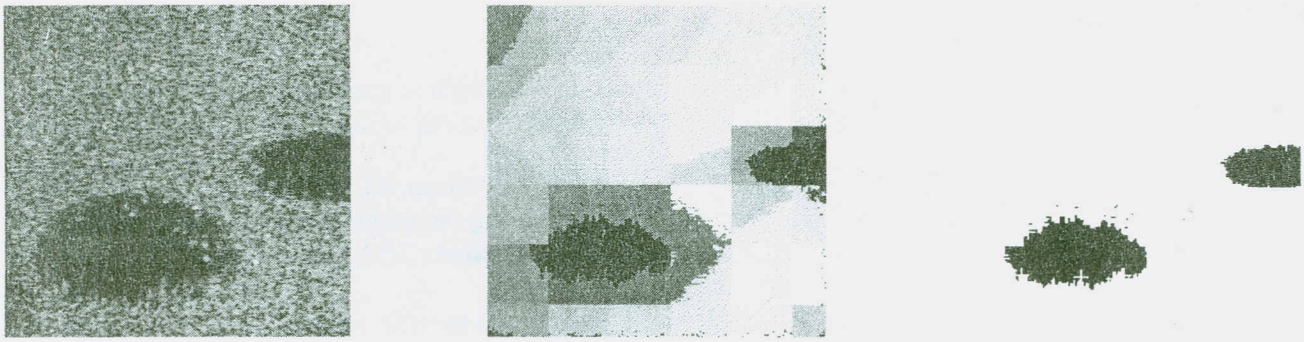
Performance of the segmentation scheme is tested on a phantom and a liver image. The *256* gray level images are segmented in *2* or *3* regions using *36x36*, *18x18*, and *9x9* windows. The results obtained from the phantom image using *36x36* windows is shown in Fig. 2. In Fig. 2.b, the segmented windows on the whole image can be clearly observed. The image shown in Fig. 2.c is segmented in *2* regions. The results from the liver image is shown in Fig. 3.a, where *3*-level segmentation is used. The structures that must be preserved are lost in some windows. Changing the location of the windows or moving the image portions gives different segmentation results. Fig. 3.b indicates that *36x36* windowing gives inefficient segmentation. To decrease this effect, smaller windows are used in the first part of the segmentation procedure. The segmentation results using *18x18* and *9x9* windows are shown in Fig. 3.c and Fig. 3.d respectively.

In Fig. 3, vein structure of the liver image can be seen as a black region and the organ boundary can be seen as a white region which is in the lower part of the image and has a curve structure. The blocking effect on the vein structure has been observed in Fig. 3.b, Fig 3.c, and Fig. 3.d. Some of the resolvable structures like small blood vessels have been lost using *36x36* and *18x18* windows as shown in Fig. 3.b and Fig. 3.c. Despite the blocking effect, small structures have been preserved using *9x9* windows as it can be seen in Fig. 3.d.

In general the test results show that performance of the segmentation increases as the window size decreases. Segmentation in an acceptable level using small windows preserves the resolvable structures.

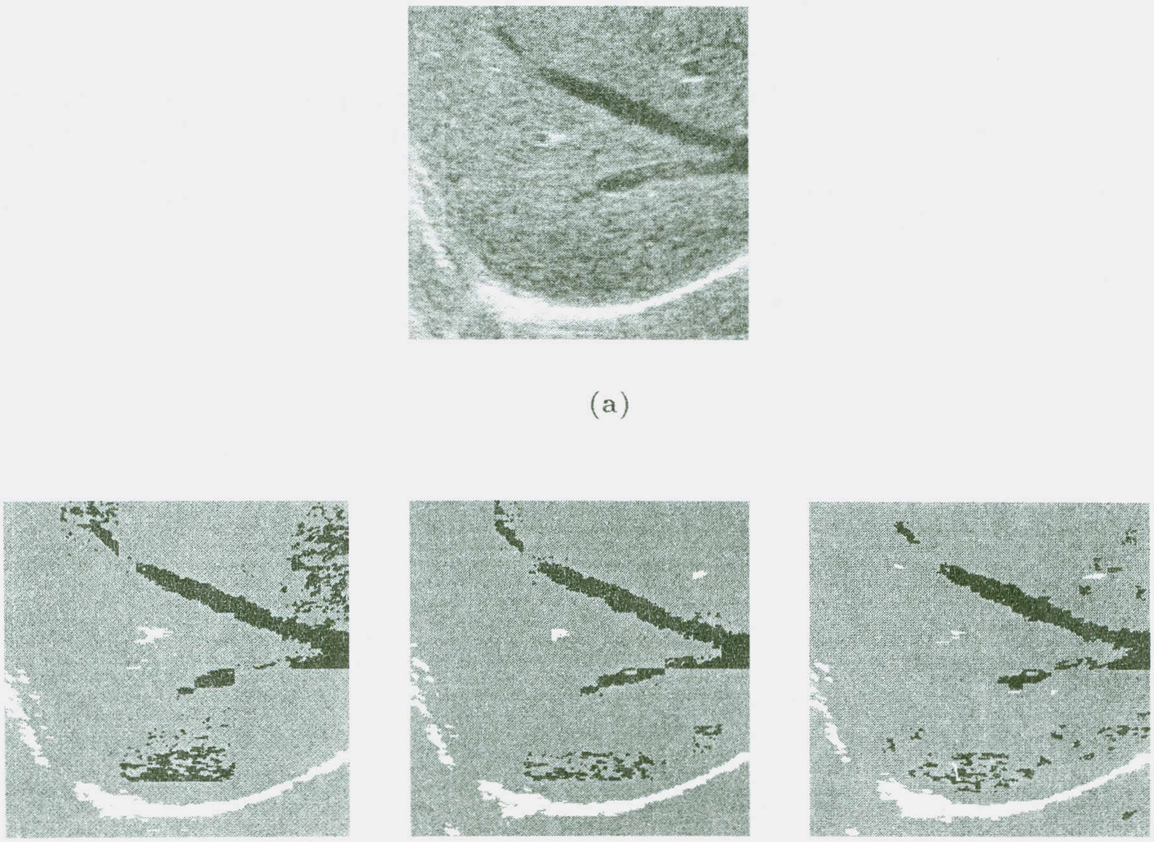
5. Conclusion

A segmentation technique based on fuzzy partitioning is investigated. The approach uses the fuzzy c-means algorithm and local statistics information. The test results on the phantom and clinical images show that B-scan images can be efficiently segmented using the investigated scheme. Future studies should focus on the further optimization of segmentation parameters.



(a) (b) (c)

Figure 2: a) The phantom image, b) The result of the segmentation procedure after the first step, 36x36 windows are used, c) The segmented phantom image in 2-level.



(a)

(b) (c) (d)

Figure 3: The liver image, (a) the original and (b) the segmented images using 36x36, (c) 18x18, and (d) 9x9 windows in 3-level.

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