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# A hybrid segmentation method based on Gaussian kernel fuzzy clustering and region based active contour model for ultrasound medical images

Deep Gupta*, R.S. Anand, Barjeev Tyagi

*Department of Electrical Engineering, Indian Institute of Technology Roorkee, Roorkee 247667, India*

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ABSTRACT

Segmentation is a very crucial task for the ultrasound medical images due to the presence of various imaging artifacts and noise. This paper presents a hybrid segmentation method for the ultrasound medical images that utilize both the features of the Gaussian kernel induced fuzzy C-means (GKFCM) clustering and active contour model driven by region scalable fitting (RSF) energy function. In this method, the result obtained from the GKFCM method is utilized to initialize the contour that spreads to identify the estimated regions. It also helps to estimate the several controlling parameters used in the curve evolution process. The RSF formulation that is responsible for attracting the contour toward the object boundaries removes the requirement of the re-initialization process. The performance of the proposed method is evaluated by conducting several experiments on both the synthetic and real ultrasound images. Experimental results demonstrate that the proposed method produces better results by successfully detecting the object boundaries and also ensures an improvement in segmentation accuracy compared to others.



## 1. Introduction

Segmentation of an ultrasound image is a process of dividing the given image into distinct regions or partitions that also have a special clinical meaning. Medical image segmentation plays a vital role in the several applications such as image visualization, quantitative analysis, image guided intervention and surgery [1]. Among the medical images obtained from different imaging modalities, ultrasound (US) imaging is a most prominent choice for the diagnosis of the living organs. This widespread choice of the US imaging is because of its cost effectiveness, acceptability, portability and safety. However, the automatic and accurate segmentation of the US images is still a challenging problem because of the poor quality of images which need further the manual intervention. Thus, accurate and automatic extractions of the region or object boundaries are in a great need for the US images.

In past years, several algorithms have been reported in the literature for image segmentation such as Markov random field [2,3], region growing [4,5], watershed [6,7], neural network [8,9], fuzzy logic [10], cell competition [11], fast marching [12], multidimensional space-frequency method, clustering [13–15] and active contour (ACM)/level set method [4,16–21] etc. Currently, lots of research work on the US image segmentation is concentrated on the active contour model. The existing active contour method can be differentiated into two types: edge based active contour model (EBACM) [17,19,22,23] and region based active contour model (RBACM) [16,18,24–28]. Geodesic active contour (GAC) method proposed by Caselles et al. [22] is most popular edge based segmentation method based on the curve evolution theory using image gradient. However, it is usually sensitive to noise and weak edges. On the other hand, Chan and Vese [16] proposed the CV method based on Mumford Shah model that is most commonly used region based active contour model for segmentation purpose. However, this model is computationally expensive, but it has much convergence range by incorporating the region-based information into the energy function. The RBACM is well suitable for the US image segmentation, if its energy function needs to be well framed. The level set method introduced by Osher and Sethian is used to capture the moving fronts in the image [17,29]. The evolution of the level set function $\varnothing$ is given by

$$\frac{\partial \varnothing}{\partial t} = F|\nabla \varnothing|, \ \varnothing_0(x, y) = \varnothing(0, x, y) \tag{1}$$

* Corresponding author. Tel.: +91 9358190782.
*E-mail addresses:* er.deepgupta@gmail.com (D. Gupta), anandfee@iitr.ac.in (R.S. Anand), btyagfee@iitr.ac.in (B. Tyagi).

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where $F = div(\nabla\varnothing/|\nabla\varnothing|)$ denotes the speed function that controls the motion of active contour, $|\nabla\varnothing|$ denotes the normal direction and $\varnothing_0$ represents the initial contour.

In the conventional level set methods, some irregularities occur during the curve evolution process. Many researchers have tried to re-initialize the regularity of the level set function (LSF) and make it stable process [30,31]. However, sometimes it moves the zero LSF away from the estimated position. In order to solve this problem, Li et al. [18] introduced a variational level set formulation with the ACM, which works on the region scalable fitting (RSF) energy function and regularization function, is used to segment the images. The RSF energy is able to obtain the intensity information in the local regions at a fixed scale by computing the two fitting functions and also drives the contour toward the estimated boundaries of the object [18]. The performance of this method is based on the proper initialization of the contour and choosing the appropriate parameters used in the LSF evolution. Furthermore, it needs the manual tracing. Thus, it becomes a very tedious job that is also time consuming and experience or knowledge dependent. Due to improper initialization of contour, different results may also be obtained using different contour on the similar image. This paper presents an automatic ultrasound image segmentation method in which the fuzzy membership function from the Gaussian kernel induced fuzzy C-means (GKFCM) with spatial constraints (GKFCM_X = GKFCM_S1 and GKFCM_S2) clustering is not used only to initialize the contour but to evaluate the contour propagation controlling parameters also. The GKFCM clustering algorithm is also able to provide better results by incorporating the kernel-induced distance in place of the Euclidean distance like conventional fuzzy C-means clustering [32].

This paper is structured as follows. Section 2 presents the background of the GKFCM clustering and RBACM-RSF segmentation methods as the same are being used to present the proposed method. Section 3 illustrates the implementation of the proposed automatic segmentation algorithm. The results of the proposed method are presented in Section 4 and also compared with others. Conclusions are drawn in the final Section 5.

## 2. Theoretical background

### 2.1. Gaussian kernel fuzzy C-means

Fuzzy clustering is used to arrange a similar data points into a same cluster, iteratively by optimizing its cost function which is based on the Euclidean distance of the pixels to centroids of the different cluster. The FCM provides good results for medical image segmentation. However, it is very sensitive to noise that affects the segmentation accuracy also. Since, it does not include the spatial information of the pixels. To eliminate the limitations of the FCM method, the authors [13] proposed the FCM_S with the new cost function by inclusion of the spatial information. Furthermore, it is extended by Chen et al. [14] to the FCM_S, FCM_S1 and FCM_S2 by incorporating the neighborhood term, mean and median filtered image, respectively. To overcome the limitation of the more computation time because of considering neighborhood terms in each step, the authors introduced the kernel induced fuzzy C-means [14] with its variants that incorporates the kernel induced distance function $\left\|\Psi(s_i) - \Psi(v_j)\right\|^2$ in place of the Euclidean distance $||s_i - v_j||^2$, where $\Psi$ is a nonlinear map from the data space into the feature space with the corresponding kernel K. The main drawback is that their parameters heavily affect the final clustering outcomes. Furthermore, clustering is concentrated on the GKFCM that is modified by Yang and Tsai [32]. Several quantitative evaluations have been performed and shown that the two different variants of GKFCM with spatial constraints known as GKFCM_X = GKFCM_S1 and GKFCM_S2 performs better than the others. The performance of the proposed method is evaluated by segmenting the image using GKFCM_X at the earlier stage. The cost function of the GKFCM_X is given by

$$J_p^{GKFCM\_X}(\mu, v) = \sum_{i=1}^{L}\sum_{j=1}^{C}\mu_{ji}^{p}(1 - K(s_i, v_j)) + \sum_{i=1}^{L}\sum_{j=1}^{C}\eta_j\mu_{ji}^{p}(1 - K(X, v_j)) \quad (2)$$

The fuzzy membership function is subject to the constraints that are given as

$$\sum_{j=1}^{C}\mu_{j,i} = 1, \quad \mu_{j,i} \in [0, 1], \quad \sum_{i=1}^{L}\mu_{j,i} > 0 \quad (3)$$

where

$$K(s_i, v_j) = \exp\left(-\frac{||s_i - v_j||}{\sigma^2}\right), \quad \sigma^2 = \frac{1}{L}\sum_{i=1}^{L}\left\|(s_i) - \left(\frac{1}{L}\sum_{i=1}^{L}(s_i)\right)\right\|^2, \quad S = (s_1, s_2, s_3, \cdots, s_L)$$

$\mu_{j,i}$ is the membership of the pixel $s_i$ in the $j$th cluster and $v_j$ is the centroid of the $j$th cluster. $||\cdot||$ is the norm of a matrix and $p$ is a weighted exponent on each fuzzy membership that controls the fuzziness of the final segmentation. The term $\eta_j$ is used to control the effect of the neighboring term for each cluster and is evaluated as

$$\eta_j = \frac{\min_{j' \neq j}(1 - K(v_{j'}, v_j))}{\max_k(1 - K(v_k, s^{Mean}))} \quad (4)$$

Thus, by minimizing the cost function $J_p^{GKFCM\_X}(\mu, v)$ of the GKFCM_X, the membership function and centroid are updated iteratively and it is given by

$$\mu_{j,i} = \frac{1}{\sum_{k=1}^{C}\left(\frac{[1-K(s_i,v_j)]+\eta_j[1-K(X,v_j)]}{[1-K(s_i,v_k)]+\eta_j[1-K(X,v_k)]}\right)^{1/p-1}} \quad (5)$$

$$v_j = \frac{\sum_{i=1}^{L}\mu_{ji}^{p}(K(s_i, v_j)s_i + \eta_j K(X, v_j)X)}{\sum_{i=1}^{L}\mu_{ji}^{p}(K(s_i, v_j) + \eta_j K(X, v_j))} \quad (6)$$

where, $X$ represents the $s_i^{Mean}$ and $s_i^{Median}$ for implementing GKFCM_S1 and GKFCM_S2, respectively. The $s_i^{Mean}$ and $s_i^{Median}$ are the averaged and median values of the neighboring pixels within a window around $s_i$, respectively.

### 2.2. RSF model

The region based active contour model using a variational level set formulation is mostly used for ultrasound medical image segmentation. The main problem in these models is that the LSF must be reinitialized periodically. Many researchers have tried in this direction to re-initialize the regularity of the level set function. However, it moves the zero LSF away from the estimated position. Furthermore, Li et al. [18] introduced a RBACM model using the new variational LSF that works on the RSF energy and level set regularization term. It is able to guide the motion of the contour toward the