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A hybrid edge-based segmentation approach for ultrasound medical images

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ABSTRACT

Ultrasound imaging is one of the most widely used and the cheapest diagnostic tools of medical imaging modalities. In this paper, a hybrid approach for accurate segmentation of the ultrasound medical images is presented that utilizes both the features of kernel fuzzy clustering with spatial constraints and edge based active contour method using distance regularized level set (DRLS) function. The result obtained from the kernel fuzzy clustering is utilized not only to initialize the curve that spreads to identify the estimated region or object boundaries, but also helps to estimate the optimal parameters, which are responsible for controlling the level set evolution. The DRLS formulation also increase the processing speed by removing the need of re-initialization of the level set function. The performance of the proposed method is evaluated by conducting the several experiments on both the synthetic and real ultrasound images. Experimental results show that the proposed method improves the segmentation accuracy and also produces better results by successfully segmenting the object boundaries compared to others.

1. Introduction

Segmentation is a process of partitioning the given image into distinct regions that have specific clinical meanings. Segmentation of medical images plays an important role in the various applications such as visualization, quantitative analysis and image-guided intervention and surgery [1]. Among the medical images obtained from different imaging modalities, ultrasound (US) imaging is most widely used for the diagnosis of several living organs. This widespread choice is because of its cost effectiveness, portability, acceptability, and safety. However, the accurate segmentation that provides the meaningful information is still a very crucial problem in the US images due to its poor quality. It needs further the manual intervention. Furthermore, an automatic and appropriate detection of the object boundaries are in a great need for the ultrasound images.

In past years, several algorithms have been reported in the literature for image segmentation such as Markov random filed [2,3], region growing [4,5], watershed [6,7], neural network [8,9], fuzzy logic [10,11], cell competition [12], fast marching [13], clustering [14–18] and active contour/level set method [4,19–25] etc. Currently, lots of research work on the ultrasound image segmentation is concentrated on the active contour model. For the implementation of active contour models, two main approaches such as snake and level set method are generally used that is based on optimization of the energy function. In the snake method, there is a problem associated with the initialization of contour and poor convergence in the noisy image because it moves the curve explicitly on predefined snake points that is based on the energy minimization model [20,26]. On the other hand, level set method presented by Osher and Sethian [27] has been shown to be effective for the image segmentation in which the partial differential equations are formulated implicitly for moving the contour by evolving the level set function (LSF) instead of directly moving the curves. The evolution equation of the level set function ∅ known as an implicit active contour [19] is defined as,

$$\frac{\partial \phi}{\partial t} = F|\nabla \phi|, \phi_0(x, y) = \phi(0, x, y) \tag{1}$$

where $F = div\left(\frac{\nabla \phi}{|\nabla \phi|}\right)$ denotes the speed function that controls the motion of active contour, $|\nabla \phi|$ denotes the normal direction and ϕ_0 represents the initial contour.

In the conventional level set methods, some irregularities occur during the evolution of the LSF. Many researchers have tried to re-initialize the regularity of the LSF and make it stable process

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[28–30]. However, sometimes it moves the zero LSF away from the estimated position. In order to solve this problem, Li et al. [22] introduced a variational formulation for the Geodesic active conotur (GAC) with a penalty term that drives the LSF to be close to the signed distance function and completely eliminates the periodic re-initialization process during the level set evolution. Furthermore, the authors [31] extended their previous method to distance regularized level set (DRLS) method by introducing a new distance regularization term provided by two well potential function and external energy term by which the contour moves towards the expected position. It also eliminates the unwanted side effect introduced on the LSF because of the penalty term present in the method [22]. The performance of the level set method is based on the proper initialization of contour and choosing the appropriate parameters used in the level set evolution. Furthermore, it needs the manual intervention. Thus, it becomes a very tedious job that is also time consuming and experience or knowledge dependent. This paper presents an automated computer assisted ultrasound image segmentation approach in which the fuzzy membership function from the kernel induced fuzzy C-means (KFCM) with spatial constraints (KFCM_X = KFCM_S1 and KFCM_S2) clustering is utilized not only to initialize the LSF but to evaluate the contour propagation controlling parameters also. The KFCM clustering 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 [17].

This paper is structured as follows. Section 2 presents the background of the KFCM clustering and the DRLS segmentation model as the same are being used to present the proposed method. Section 3 illustrates the implementation of the proposed method. The experimental results are discussed in Section 4 and also compared with others. Conclusions are drawn in the final Section 5.

2. Methods

2.1. Kernel fuzzy C-means clustering

Fuzzy C-means (FCM) is used to group similar data points into a same cluster iteratively by minimizing its cost function that is based on the Euclidean distance of the pixel 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 [16] have introduced the FCM_S with the new cost function by inclusion of the spatial information. Furthermore, it extends to the FCM_S1 and FCM_S2 by incorporating the mean and median filtered image, respectively [17]. To overcome the limitation of more computation time because of considering neighborhood terms in each step, two different variants of the KFCM with the spatial constraints known as KFCM_X i.e. KFCM_S1 and KFCM_S2 [17]. In the KFCM clustering, the Euclidean distance $\|s_i - v_j\|^2$ is replaced by the kernel induced distance function $\|\Psi(s_i) - \Psi(v_j)\|^2$, where Ψ is a nonlinear map from the data space into the feature space with the corresponding kernel K. The performance of the proposed method is evaluated by segmenting the image using KFCM_X at the earlier stage. The cost function of the KFCM_X is given as

$$J_p^{KFCM\_X}(\mu, v) = \sum_{i=1}^{L}\sum_{j=1}^{C}\mu_{j,i}^{p}\left(1 - K\left(s_i, v_j\right)\right) + \eta\sum_{i=1}^{L}\sum_{j=1}^{C}\mu_{j,i}^{p}\left(1 - K\left(X, v_j\right)\right) \quad (1)$$

The fuzzy membership functions are subject to the following constraints

$$\sum_{j=1}^{C}\mu_{j,i} = 1,\ \mu_{j,i} \in [0, 1],\ \sum_{i=1}^{L}\mu_{j,i} > 0 \quad (2)$$

where $K\left(s_i, v_j\right) = \exp\left(-\frac{\|s_i - v_j\|^2}{\sigma^2}\right)$, $\sigma^2 = \frac{1}{L}\sum_{i=1}^{L}\left\|(s_i) - \left(\frac{1}{L}\sum_{i=1}^{L}s_i\right)\right\|^2$, $S = (s_1, s_2, s_3, \ldots, s_L)$, $\mu_{j,i}$ is the membership of the pixel s_i in the jth cluster and v_j is the centroid of the jth 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.

Thus, by minimizing the objective function $J_p^{KFCM\_X}(\mu, v)$ of the KFCM_X, the membership function $\mu_{j,i}$ and centroid v_j are updated iteratively and these are given by

$$\mu_{j,i} = \frac{1}{\sum_{k=1}^{C}\left(\frac{[1-K(s_i,v_j)]+\eta[1-K(X,v_j)]}{[1-K(s_i,v_k)]+\eta[1-K(X,v_k)]}\right)^{1/p-1}} \quad (3)$$

$$v_j = \frac{\sum_{i=1}^{L}\mu_{ji}^{p}\left(K\left(s_i, v_j\right)s_i + \eta K\left(X, v_j\right)X\right)}{\sum_{i=1}^{L}\mu_{ji}^{p}\left(K\left(s_i, v_j\right) + \eta K\left(X, v_j\right)\right)} \quad (4)$$

where, X represents the s_i^{Mean} and s_i^{Median} for implementing KFCM_S1 and KFCM_S2, respectively. The s_i^{Mean} and s_i^{Median} are the average and median values of the neighboring pixels within a window around s_i, respectively.

2.2. Distance regularized level set segmentation model

The level set method is widely used to solve the problem of dynamic variation boundaries for ultrasound image segmentation. Firstly, the level set model is introduced by Osher and Sethian for capturing moving fronts [22,27]. Furthermore, Li et al. extended the conventional level set formulation to distance regularized level set (DRLS) formulation by incorporating the new distance regularizing term with double well potential function. Thus, the DRLS formulation is defined as follows,

$$E_{Total}(\phi) = \mu R(\phi) + E_{ext}(\phi) \quad (5)$$

where the overall energy $E_{Total}(\phi)$ consists of two parts: $R(\phi)$ refers the regularization term which forces ϕ to automatically approach the signed distance function during the evolution of the LSF, $E_{ext}(\phi) = \lambda L(\phi) + \alpha A(\phi)$ is the external energy that forces the zero level set function to the expected position. The parameter $\mu > 0$ is the weighting coefficient of the regularization term. The parameter $\lambda > 0$ is a weighting coefficient of the contour length to control the smoothness of the contour during evolution and the other weighting coefficients α can be positive or negative depending upon the relative position of the initial contour. The energy functional terms can be defined as follows,

$$L(\phi) \triangleq \int_{\Omega} g\delta_{\varepsilon}(\phi)|\nabla\phi|dx \quad (6a)$$

$$A(\phi) \triangleq \int_{\Omega} gH_{\varepsilon}(-\phi)dx \quad (6b)$$