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Optimized Kernel Fuzzy C-Means Clustering for Bio-Images Using Level Set Method

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***Abstract* – In this paper, optimized kernel fuzzy c-means (OKFCM) was used to generate an initial contour curve which overcomes leaking at the boundary during the curve propagation. Firstly, OKFCM algorithm computes the fuzzy membership values for each pixel. On the basis of OKFCM the edge indicator function was redefined. Using the edge indicator function the bio- segmentation of a medical image was performed to extract the regions of interest for advance processing. In this process the complexity of time iteration is reduce compare to better than KFCM. The above process of segmentation showed a considerable improvement in the evolution of the level set function.**

***Keywords* – Image Segmentation, Bio-Images, OKFCM, Level Set Method.**

I. Introduction

Image segmentation is plays an important role in the field of image understanding, image analysis, pattern identification. The foremost essential goal of the segmentation process is to partition an image into regions that are homogeneous (uniform) with respect to one or more self characteristics and features. Clustering has long been a popular approach to untested pattern recognition. The fuzzy c-means (FCM)[1] algorithm, as a typical clustering algorithm, has been utilized in a wide range of engineering and scientific disciplines such as medicine imaging, bioinformatics, pattern recognition, and data mining. *Given* a data $X = \{x_i .... x_n\} \subset R^p$, the original FCM algorithm partitions X into c fuzzy subsets by minimizing the following objective function

$$J_m(U, V) \equiv \sum_{i=1}^{c} \cdot \sum_{k=1}^{n} u_{ik}^m \|x_i - v_i\|^2 \quad .... (1)$$

Where c is the number of cluster and selected as a specified

Value in the paper, n the number of data points, u_k , the member of x_k in class i , satisfying $\sum_{i=1}^{c} u_{ik}$, m the quantity controlling clustering fuzziness and v is set of control cluster centers or a prototypes $\left(v_i \in R^p\right)$. The function J_m is minimized by the famous alternate iterative algorithm. Since the original FCM uses the squared-norm to measure inner product with an appropriate 'kernel' function, one similarity between prototypes and data points, it can only be effective in clustering 'spherical' clusters. And many algorithms are resulting from the FCM in order to cluster more general dataset. Most of those algorithms are realized by replacing the squared-norm in Eq (1) the object function of FCM with other similarity trial (metric) [1-2]. In this paper, a optimized kernel-based fuzzy c-means algorithm (OKFCM) is projected. OKFCM adopt a new kernel-induced metric in the data space to restore the original Euclidean norm metric in FCM. By replacing the inner product with an appropriate 'kernel' function, one can absolutely perform a nonlinear mapping to a high dimensional feature space without increasing the number of parameters.

The level set method is [4-7] based on geometric deformable model, which translate the problem of evolution 2-D (3-D) close curve(surface) into the evolution of level set function in the space with higher dimension to obtain the advantage in managing the topology changing of the shape. The level set method has had great success in computer graphics and vision. Also, it has been widely used in medical imaging for segmentation and shape recovery [8-9]. However, there are some insufficiencies in traditional level set method.

Firstly, as using the local marginal information of the image, it is difficult to obtain a perfect result when there's a fuzzy or discrete boundary in the region, and the leaking problem is unescapably appeared; Secondly, solving the partial differential equation of the level set function requires numerical processing at each point of the image domain which is a time consuming process; Finally, if the initial evolution contour is given at will, the iteration time would increase greatly, too large or too small contour will cause the convergence of evolution curve to the contour of object incorrectly. Therefore, some modification has been proposed to improve the speed function of curve evolution [10-12]. In the paper, based on the new variational level set method, the edge indicator function was weighted to improve the ability of detecting fuzzy boundaries of the object. At the same time, the KFCM algorithm [13-14] was applied to obtain the appropriate initial contour of evolution curve, so as to get the accurate contour of object and reduce the evolution time.

II. Optimized Kernel Fuzzy C-Means Clustering (OKFCM)

Define a nonlinear map as $\phi : x \to \phi(x) \in F$,where

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$x \in X$. X denotes the data space and F is the transformed feature space with higher even infinite dimensions. OKFCM minimized the following objective function:

$$J_m(U,V) \equiv \sum_{i-1}^{c} \cdot \sum_{k-1}^{n} u_{ik}^{m} \left\| \phi(x_i) - \phi(v_i) \right\|^2 \quad \text{........ (2.2)}$$

Where

$$\left\| \phi(x_i) - \phi(v_i) \right\|^2 = K(x_k, x_k) + K(v_i, v_i) - 2K(x_k, v_i) \quad \text{.................... (2.3)}$$

Where $K(x, y) = \phi(x)^T \phi(y)$ is an inner product of the kernel function. If we adopt the Gaussian function as a kernel function, $K(x,y) = \exp\left(-\|x-y\|^2 / 2\sigma^2\right)$, then $K(x,x) = 1$. according to Eq. (2.3), Eq. (2.2) can be rewritten as

$$J_m(U,V) \equiv 2\sum_{i-1}^{c} \cdot \sum_{k-1}^{n} u_{ik}^{m} \left(1 - k(x_k, v_i)\right). \quad \text{.......... (2.4)}$$

Minimizing Eq. (2.4) under the constraint of, $u_{ik}, m > 1$. We have

$$u_{ik} = \left[\frac{\left(1/\left(1-K\left(x_k, v_i\right)\right)\right)^{1/(m-1)}}{\sum_{j=1}^{c} \left(1/\left(1-K\left(x_k, v_i\right)\right)\right)^{1/(m-1)}} \right]^{\frac{1}{2}} \quad \text{.......... (2.5)}$$

$$v_i = \frac{\sum_{k=1}^{n} u_{ik} K(x_k, v_i) x_k}{\sum_{k=1}^{n} u_{ik}^{m} K(x_k, v_i)} \quad \text{...................... (2.6)}$$

Here we now utilize the Gaussian kernel function for Straightforwardness. If we use additional kernel functions, there will be corresponding modifications in Eq. (2.5) and (2.6).

In fact, Eq.(2.3) can be analyzed as kernel-induced new metric in the data space, which is defined as the following

$$d(x,y) \underline{\underline{\Delta}} \left\| \phi(x) - \phi(y) \right\| = \sqrt{2\left(1 - K(x,y)\right)} \quad \text{........ (2.7)}$$

And it can be proven that $d(x, y)$ is defined in Eq. (2.7) is a metric in the original space in case that $K(x, y)$ takes as the Gaussian kernel function. According to Eq. (6), the data point x_k is capable with an additional weight $K(x_k, v_i)$, which measures the similarity between x_k and v_i and when x_k is an outlier i.e., x_k is far from the other data points, then $K(x_k, v_i)$ will be very small, so the weighted sum of data points shall be more strong.

The full explanation of OKFCM algorithm is as follows:

OKFCM Algorithm:

Step 1: Select initial class prototype $\{v_i\}_{i=1}^{c}$.

Step 2: Update all memberships u_{ik} with Eq. (2.5).

Step 3: Obtain the prototype of clusters in the forms of weighted average with Eq. (2.6).

Step 4: Repeat step 2-3 till termination. The termination criterion is $\left\| V_{new} - V_{old} \right\| \le \varepsilon$.

Where $\|.\|$ is the Euclidean norm. V is the vector of cluster centers ε is a small number that can be set by user (here ε =0.01).

III. The Modification to the Level Set Method

The level set method was invented by Osher and Sethian [4] to hold the topology changes of curves. A simple representation is that when a surface intersects with the zero plane to give the curve when this surface changes, and the curve changes according with the surface changes. The heart of the level set method is the implicit representation of the interface. To get an equation describing varying of the curve or the front with time, we started with the zero level set function at the front as follows:

$$\phi(x, y, t) = 0, \text{ if } (x, y) \in 1 \quad \text{.......(3.1)}$$

Then computed its derivative which is also equal to zero

$$\frac{\partial \phi}{\partial t} + \frac{\partial \phi}{\partial x} \cdot \frac{\partial x}{\partial t} + \frac{\partial \phi}{\partial y} \cdot \frac{\partial y}{\partial t} = 0 \quad \text{..........(3.2)}$$

Converting the terms to the dot product form of the gradient vector and the x and y derivatives vector, we go

$$\frac{\partial \phi}{\partial t} + \left(\frac{\partial \phi}{\partial x} \cdot \frac{\partial x}{\partial t} \right) \bullet \left(\frac{\partial \phi}{\partial y} \cdot \frac{\partial y}{\partial t} \right) = 0 \quad \text{........(3.3)}$$

Multiplying and dividing by $\nabla \phi$ and taking the other part to be F the equation was gotten as follows:

$$\frac{\partial \phi}{\partial t} + F\left| \nabla \phi \right| = 0 \quad \text{............(3.4)}$$

According to literature [9]11], an energy function was defined:

$$E(\phi) = \mu E_{\text{int}}(\phi) + E_{ext}(\phi) \quad \text{.......(3.5)}$$

Where $E_{ext}(\phi)$ was called the external energy, and $E_{\text{int}}(\phi)$ was called the internal energy. These energy functions were represented as:

$$E_{\text{int}}(\phi) = \int_{\Omega} \frac{1}{2} (\nabla \phi - 1)^2 \, dxdy \quad \text{............ (3.6)}$$

$$E_{ext}(\phi) = \lambda L_g(\phi) + v A_g(\phi) \quad \text{............. (3.7)}$$

$$L_g = \int_{\Omega} g \delta(\phi) \left| \nabla \phi \right| dxdy \quad \text{.............. (3.8)}$$

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$$A_g = \int_{\Omega} gH(-\phi)dxdy \quad \ldots\ldots\ldots\ldots\ldots \text{(3.9)}$$

$$g = \frac{1}{1+|\nabla G_\sigma * I|} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(3.10)}$$

Where $L_g(\phi)$ was the length of zero level curve of ϕ; and A_g could be viewed as the weighted area; I was the image and g was the edge indicator function. In conventional(traditional) level set methods, it is numerically necessary to keep the evolving level set function close to a signed distance function[15][16]. Re-initialization, a technique for occasionally re-initializing the level set function to a signed distance function during the evolution, has been extensively used as a numerical remedy for maintaining stable curve evolution and ensuring desirable results.

From the practical viewpoints, the re-initialization process can be quite convoluted, expensive, and has subtle side effects [17]. In order to overcome the problem, Li et al [9] proposed a new variational level set formulation, which could be easily implemented by simple finite difference scheme, without the need of re-initialization. The details of the algorithm are in the literature [9]. However, because only the gradient information was imposed in the edge indicator function, Li's method has a little effect on the presence of fuzzy boundaries.

In the paper, a innovative method was proposed to modify the algorithm. The original image was partitioned into some sub images by OKFCM. The fuzzy boundary of each sub image was weighted by α, the edge indicator function was redefined:

$$g' = g + \alpha \cdot g_2 \ldots\ldots\ldots\ldots\ldots\ldots \text{(3.11)}$$

Where $g_2 = \dfrac{1}{1+|\nabla G_\sigma * I_1|}$

I_1 Was the image after clustering. The iterative equation of level set functional was:

$$\frac{(\phi^{n+1}-\phi^n)}{\tau} = \mu\left[\Delta\phi - div\left(\frac{\nabla\phi}{|\nabla\phi|}\right)\right] + \lambda\delta(\phi)div\left(g'\frac{\nabla\phi}{|\nabla\phi|}\right) + vg'\delta(\phi)$$

……... (3.12)

Taking $g' = g + \alpha \cdot g_2$ into 3.12

$$\phi^{n+1} = \phi^n + \tau\left\{\begin{array}{l} \mu\left[\nabla\phi - div\left(\frac{\nabla\phi}{|\nabla\phi|}\right)\right]\lambda\delta(\phi)div\left(g\frac{\nabla\phi}{|\nabla\phi|}\right) \\ +vg\delta(\phi)+\alpha\left[\begin{array}{l}\lambda\delta(\phi)div\left(g_2\frac{\nabla\phi}{|\nabla\phi|}\right)+ \\ vg_2(\phi)\end{array}\right]\end{array}\right\}\ldots$$

……………………… (3.13)

Where $\alpha \in [0,1]$. When processing images of weak boundary or low contrasts, a bigger α was taken; otherwise, a smaller α was taken.

III. The Generation of Initial Contour Curve

On the basis of KFCM clustering [3] in image segmentation, the over segmentation usually exists. In this paper, the result of OKFCM was used as initial contour curve, and the automated initialization of twist model was finished.

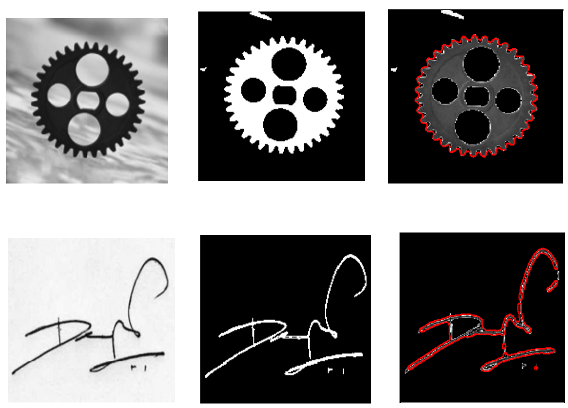
For all the pixels in each cluster i.e. white matter, if 4 neighborhoods included the heterogeneous pixel, the pixel was regarded as candidate boundary point. Some pixels, such as noise points, might be included in the candidate boundary points. So the algorithm of curve tracing [18] was proposed. The exterior boundary of the cluster was tracked in the candidate boundary points. Finally, the closed curve was obtained. The candidate boundary points, whose Euclidean distances to the origin coordinates were shortest, were chosen as initiation points of curve tracing. The steps of image segmentation with adapted level set method were as follows:

Step1. Set the number of clusters, then the original image was processed with OKFCM, and calculate the g_2.

Step2. Choose one cluster, evaluate the inside area with $-\rho$ and the outside area with $+\rho$, ρ is a plus constant. The boundary of the area is set to 0. The region of interest is defined initial contour.

Step3. Minimize the overall energy functional with 3.13 formula.

IV. Experimental Results of Perfect Locked Test Images



This test images shows the perfect locked region of interest of particular images as shown in figures above for OKFCM and final contour with proposal.

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V. Experimental Results

The segmentation of image takes an important branch in the surgery navigation and tumor radiotherapy. However, due to medical imaging characteristics, the low contrast and fuzzy boundary is usually occurred in the images. In the experiment, the samples of images are taken from internet as shown in Figure i. The approximate contour of white matter was got by OKFCM algorithm shown in Figure ii. The snooping of regions else appear as a result of the in excess of segmentation. The initial evolution curve was obtained by the automated initialization. Because of the improved edge indicator function, the curve regularly evolved to the object boundaries in the process of evolution. The result established that the improved algorithm can extract the contour of object enhanced.

Input image OKFCM segmented Final contour

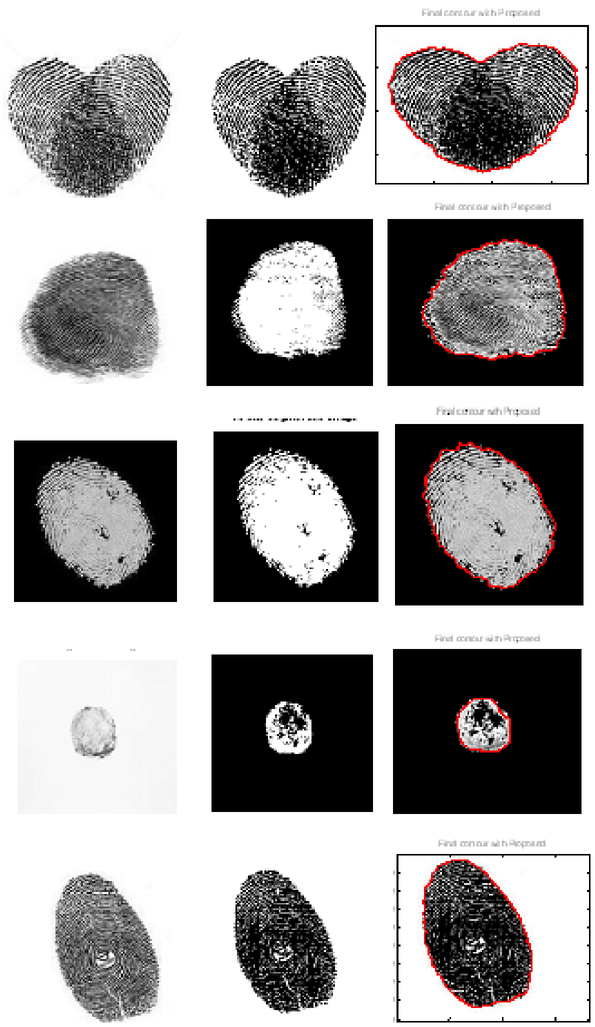

Figure i Figure ii Figure iii

Fig.(i) are the **original test images**, (ii) are the **results of OKFCM** clustering , to extracting the white matter. (iii) are the results of final contour with proposed method**.**

With the enhanced method, the curve was successfully evolved to the hollow white matter boundaries, but only to the approximately white matter boundaries with Li's method. At the same time, because the curve has been converged to the narrow region the object boundaries extraction could not be implemented with Li's method. But the enhanced method solved this problem better. On the similar computing proposal, under a 3.0GHz Pentium iv PC with 1 GB RAM on board, the average processing time of improved method was 9.6s, and that was 30.3s with Li's method. The evolution time was greatly reduced

VI. Discussions

The need of the re-initialization is completely eliminated by the proposal of Chunming Li, for pure partial differential equation driven level set methods, the variational level set methods. It can be easily implemented by using simple finite difference method and is computationally more efficient than the traditional level set methods. But, in this algorithm, the edge indicator has little effect on the low contrast image. So it is hard to obtain a perfect result when the region has a fuzzy or discrete boundary. Meanwhile, the initial contour of evolution needs to be determined by manual, and it has the shortcomings of time-consuming and user intervention.

In this paper, we projected a new method to transform the algorithm. The original image was partitioned with OKFCM, and the controlled action of the edge indicator function was increased. The result of OKFCM segmentation was used to obtain the initial contour of level set method. With the new edge indicator function, results of image segmentation showed that the improved algorithm can exactly extract the corresponding region of interest. Under the same computing proposal, the average time cost was lower. The iterative tim e of the OKFCM algorithm is reduced compared to KFCM algorithm. Alternatively the OKFCM clustering is sensitive to noise; some redundant boundaries were appeared in the candidates. Consecutively to solve this problem, the algorithm of curve tracing was proposed.

VII. Conclusions

In this paper, we proposed a kernel-induced new metric to replace the Euclidean norm in fuzzy c-means algorithm in the original space and then derived the alternative kernel-based fuzzy c-means algorithm. The results of this paper confirmed that the mixture of OKFCM with the level set methods could be used for the segmentation of low contrast images and medical images. The method has the advantages of no reinitialization, automation, and reducing the number of iterations. The validity of new algorithm was verified in the process of exacting details of images. In the future research, noise was added in images prior information on the object boundary extraction with level set method, such as boundary, shape, and size, would

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be further analyzed. At the same time, the performance of image segmentation algorithms would be improved by modernization of classic velocity of level set method.

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