International Journal of Engineering Technology Science and Research
IJETSR
www.ijetsr.com
ISSN 2394 – 3386
Volume 4, Issue 5
May 2017

Modified Improved Kernel Fuzzy Adaptive Threshold Algorithm on Modified Level set method for Picture Segmentation

T.Saikumar[1], G.SudhaRani[2], K.Keerthi[2],K.Sneha[2],B.Srikar[2]
[1]Associate Professor, Department of Electronics & Communication Engineering
[2]B.Tech Final Year Students, Department of Electronics & Communication Engineering
CMR Technical Campus, Hyderabad, India

Abstract— Using thresholding method to segment an image, a fixed threshold is not suitable if the background is rough Here, we propose a new adaptive thresholding method using level set theory. The method requires only one parameter to be selected and the adaptive threshold surface can be found automatically from the original image. An adaptive thresholding scheme using adaptive tracking and morphological filtering. The Improved Kernel fuzzy c-means (IKFCM) was used to generate an initial contour curve which overcomes leaking at the boundary during the curve propagation. MKFCM algorithm computes the fuzzy membership values for each pixel. On the basis of MKFCM the edge indicator function was redefined. Using the edge indicator function of a image was performed to extract the boundaries of objects on the basis of the presegmentation. Therefore, the proposed method is computationally efficient. Our method is good for detecting large and small images concurrently. It is also efficient to denoise and enhance the responses of images with low local contrast can be detected. The efficiency and accuracy of the algorithm is demonstrated by the experiments on the images. The above process of segmentation showed a considerable improvement in the evolution of the level set function.

Keywords- Adaptive thresholding, Image segmentation, MKFCM, Level set method.

I. INTRODUCTION

Thresholding techniques are often used to segment images consisting of dark objects against bright backgrounds, or vice versa. It also offers data compression and fast data processing [1]. The simplest way is through a technique called global thresholding, where one threshold value is selected for the entire image, which is obtained from the global information. However, when the background has non-uniform illumination, a fixed (or global) threshold value will poorly segment the image. Thus, a local threshold value that changes dynamically over the image is needed. This technique is called adaptive thresholding.

Basically these techniques can be divided into region-based and edge-based thresholding. Region-based technique uses the whole image to extract the information for the threshold value computation, while edge-based technique is based on the attributes along the contour between the object and the background.

For region-based technique, most of the early introduced techniques are based on the image histogram. In 1979, Otsu [2] presented a technique that considered the image histogram as having a two gaussian distribution representing the object and the background. A threshold is selected to maximize the inter-class separation on the basis of the class variances.

For the edge-based thresholding technique, the idea of applying the boundary based attributes is based on the fact that discriminate features exist at the boundary between the object and the background [3]. Thus, the edge-based thresholding technique has become more popular for exploration. Milgram [10] applied edge information to segment images by proposing "superslice" method. In this method, the edge information (gradient) is integrated with the recursive region splitting technique. The superslice method was also applied and improved in [3, 11].

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.

II. ADAPTIVE THRESHOLDING

We adapt this technique with some optimization. The following outlines Hoover's adaptive thresholding:

1) Binarize the image with a single threshold *T*

2) Thin the thresholded image

3) Erase all branchpoints in the thinned image

4) All remaining endpoints are placed in the probe queue and are used as a starting point for tracking

5) Track the region with threshold *T*

6) If the region passed testing, *T*=*T*-1, go to 5)

The testing in step 6) is some constraints to guarantee the region is image segment .Very small segments that remain after thresholding will be "size-filtered". But this step is preceded by the application of morphological filter to fill the small gaps between image.

III. MODIFIED IMPROVED KERNEL FUZZY C-MEANS CLUSTERING (MKFCM):

Define a nonlinear map as $\phi : x \rightarrow \phi(x) \in F$,where $x \in X . X$ denotes the data space and F is the transformed feature space with higher even infinite dimensions. IKFCM minimized the following objective function:

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

Where

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

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

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

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

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

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

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

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

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

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 MKFCM algorithm is as follows:

MKFCM 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 $\|V_{new} - V_{old}\| \le \varepsilon$.

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).

IV. The Modification To The Level Set Method

The level set method was invented by Osher and Sethian [4] to handle 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:

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

Then computed its derivative which is also equal to zero

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

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

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

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

$$\frac{\partial \phi}{\partial t} + F|\nabla \phi| = 0 \ldots\ldots\ldots\ldots (3.4)$$

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

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

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:

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

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

$$L_g = \int_{\Omega} g\delta(\phi)|\nabla \phi| dxdy \ldots\ldots\ldots\ldots\ldots (3.8)$$

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

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

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 traditional level set methods, it is numerically necessary to keep the evolving level set function close to a signed distance function[14][15]. Re-initialization, a technique for periodically 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 [19]. 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].

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

$$g' = g + \alpha g_2 \ldots\ldots\ldots\ldots\ldots\ldots (3.11)$$

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:

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

$\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots$ (3.12)

International Journal of Engineering Technology Science and Research
IJETSR
www.ijetsr.com
ISSN 2394 – 3386
Volume 4, Issue 5
May 2017

Taking the $g^{'} = g + \alpha g_2$ into 3.12

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

…………………………………… (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.

V. The Generation Of Initial ContourCurve

On the basis of MKFCM clustering [20] in image segmentation, the over segmentation usually exists. In this paper, the result of MKFCM 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 MKFCM, 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.

VI. Experimental Results

The segmentation of image takes an important branch in the surgery navigation and tumor radiotherapy. In the experiment, The image data from the IBSR(Internet Brain Segmentation Repository) are included to test the accuracy and efficiency of the proposed algorithm. The output of adaptive threshold algorithm and MKFCM, figure 1 is as shown below. Firstly the original MRI brain image is as shown in figure (i) is transformed to a proposed adaptive threshold algorithm with the test images of the brain and original binary image, note the over segmentation. The approximate contour of white matter was got by adaptive threshold algorithm shown in Figure ii of Figure 1. The output of adaptive threshold algorithm is given to MKFCM clustering to get the fuzzy image with fuzzy boundaries.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.

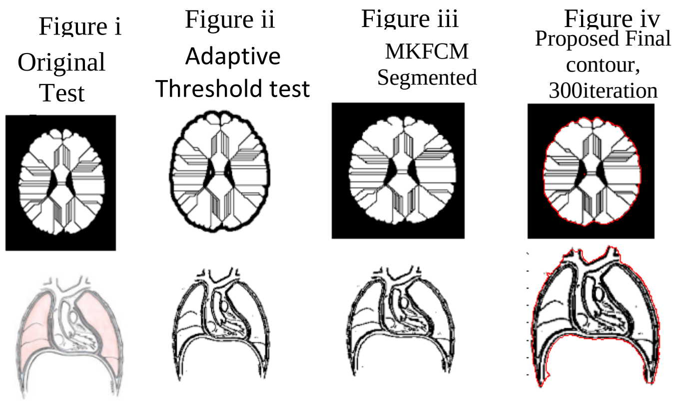

Figure: 1

Figure i are the **original test images.**

Figure ii are the **results of Adaptive threshold images,** to extracting the white matter.

Figure iii are the **results of MKFCM Segmented outputs.**

Figure iv 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.

VII. 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 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 adaptive threshold algorithm. MKFCM and the controlled action of the edge indicator function were increased. The result of adaptive threshold algorithm and MKFCM 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. Alternatively the adaptive threshold algorithm is sensitive to noise; some redundant boundaries were appeared in the candidates. Consecutively to solve this problem, the algorithm of curve tracing was proposed.

VIII. CONCLUSIONS

In this paper, we proposed an adaptive threshold algorithm, KFCM with a level set method. The results of this paper confirmed that the mixture of adaptive threshold, MKFCM 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 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.

REFERENCES

[1] A. Shio, "An Automatic Thresholding Algorithm Based On An Illumination-Independent Contrast Measure", *IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, pp. 632-637, 4-8 June 1989.

[2] N. Otsu, "A Threshold Selection Method from Gray-Level Histogram", *IEEE Trans. on System Man Cybernetics, SMC*, vol. 9(I), pp. 62-66, 1979.

[3] F.H.Y. Chan, F.K. Lam, Hui Zhu, "Adaptive Thresholding By Variational Method", *IEEE Transactions on Image Processing*, vol. 7, no. 3, pp. 468-473, March 1998.

[4] Osher, S., and Sethian J.A., "*Front Propagating with Curvature-Dependent Speed: Algorithms Based on Hamilton-Jacobi Formulations*", Journal of Computational Physics, 79, pp. 12-49, 1988.

[5] Osher, S., and Sethian J.A., "Front Propagating with Curvature-Dependent Speed: Algorithms Based on Hamilton-Jacobi Formulations", Journal of Computational Physics, 79, pp. 12-49, 1988.

[6] Malladi,R.,Sethain,J. and Vemuri,B., "Shape modelling with front propagation: A level set approach". *IEEE Trans.Pattern Analysis and Machine .Intelligence*, pp.158-174,1995.

[7] L. Staib, X. Zeng, R. Schultz and J. Duncan. "Shape Constraints in Deformable Models". *In Handbook of Medical Imaging*, I. Bankman (ed.), Academic Press, chapter 9, pp 147-157, 2000.

[8] Leventon.M, Faugeraus.O, Grimson.W, and Wells.W, "Level set based segmentation with intensity and curvature priors". *IEEE Workshop on Mathematical Methods in Biomedical Image Analysis Proceedings*, pp.4-11,2000.

[9] Paragios.N, Deriche. R, "Geodesic active contours and level sets for the detection and tracking of moving objects". *IEEE Transaction on pattern Analysis and Machine Intelligence*, pp.266-280 Mar 2000.

[10] Vese .L .A, Chan .T. F, "A multiphase level set frame wor for image segmentation using the mumford and shah model". *International Journal of Computer Vision*, vol 50 no 3,pp.271-293,2002.

[11] D. L. Milgram, “Region Extraction Using Convergent Evidence”, *IEEE Trans. on Computer Graphics and Image Processing*, vol. 11 no. 1, 1979.

[12] S. D. Yanowitz and A. M. Bruckstein, “A New Method For Image Segmentation”, *IEEE Trans. on Computer. Vision, Graphic and Image Processing*, vol. 46, pp. 82-95, 1989.

[13] Li C., Xu C., Gui C., Fox, MD: “Level set evolution without re-initialization:a new varitional formulation”. IEEE Computer Society Conference on Computer Vision and pattern Recognition,pp.430-436,2005.

[14] Bezedek J., “A convergence thheorem for the fuzzy ISODATA clustering algorthims”. *IEEE Trans.Pattern Analysis and Machine Intelligence*,pp 78-82,1980.

[15] S.Osher and R.Fedkiw, “Level set methods and Dynamic implicit surfaces”,Springer,vol 57, issue 3, pp.112-113,2002.

[16] D.Peng,B.Merriman,S.Osher,H.Zhao, and M.Kang, “A PDE- based fast local level set method”, Journal of Computational Physics,vol 155,issue 2,pp.410-438,1996.

[17] J. C. Bezdek, “*Pattern Recognition with Fuzzy Objective Function Algorithms*’’. Plenum Press, New-York, 1981.

[18] K.L.Wu, and M.S.Yang, “Alternative c-means clustering algorthims”,Pattern Recognition, vol.35, pp.2267-2278,2002.

[19] T. McInerney and D. Terzopoulos, "Deformable models in medical image analysis: a survey," *Medical Image Analysis*, vol. 1, no. 2, pp. 91-108, 1996.

[20] J.Gomes and O.Faugeras, “Reconciling distance functions and Level Sets”, J.Visual Communic. And Image Representation,vol 11, pp.209-223,2000.

[21] Zhang, L., Zhou,W.D., Jiao. L.C.: “Kernel Clustering Algorithm”. Chinese J. Computers, vol25 (6), pp. 587-590, 2002 .