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Improved Fast Two Cycle by using KFCM Clustering for Image Segmentation

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***Abstract*- Among available level set based methods in image segmentation, Fast Two Cycle (FTC) model is efficient and also the fastest one. But its efficiency is highly dependent to contour initialization. This paper tries to improve this method by using a kernel-based fuzzy c-means (KFCM) clustering algorithm. The proposed approach consists of two successive stages for image segmentation. Firstly, the KFCM is used to cluster the input image. Then ROI's fuzzy membership matrix is used for next stage as an initial contour. Eventually, FTC model is utilized to segment the image by curve evolution based on level set. As a result, two benefits are provided for image segmentation in addition of advantages of FTC model. They are independency of curve initialization and reduction of user intervention. Experimental results show promising outputs in segmentation of different kinds of image including medical data imagery, natural scene and synthetic data.**

***Index Terms*— Image Segmentation, Curve Evolution, Kernel-based Fuzzy C-Means Clustering, Geometric Active Contours, Level Set**

I. INTRODUCTION

Segmentation is a crucial step in image analysis and effect on the efficiency of image analysis extremely[1]. There are some factors that make segmentation complex such as noise, contrast variation, inhomogeneity of object boundary, motion blurring artifacts and so on [2] . These factors cause to develop a plenty of researches and several approaches in image segmentation. Moreover some tools are available for segmentation of different kind of image like medical images[3]. Nevertheless it has been remained a challenging area yet. There are a highly growing interest in this field as well[4].

Among available segmentation methods, Level set-based geometric active contour by using the theory of curve evolution shows promising results in complicated images like medical images[5]. Because it can capture the topology of shapes and are robust in noisy images. But this method [5, 6] has some drawbacks. Some researches proposed several level set-based methods to solve them. Consequently, seven different level-set algorithms were formed. Each method can solve a part of drawbacks but cause some other problems.

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Table 1 presents problems of level set based methods and corresponding available method to solve it.

Fast Two Cycle Algorithm with Smoothness Regularization which has been proposed by Shi and Karl [7], is the fastest method among level-set based ones while retaining significant accuracy[2]. So it can be called as the most efficient level-set based method which has ever been proposed. But its result is high dependent on curve initialization. In fact, initial curve doesn't consider any topological constraints but should enclose the region of interest (ROI) and touch every object and background region. Figure 1 shows the dependency of FTC Model on curve initialization in different kinds of images including medial data (first row), real data (second row) and synthetic one (third row). From left to right, an improper curve initialization in the first column leads to wrong segmentation in second column. While a proper one in the third column results in accurate segmentation in forth column.

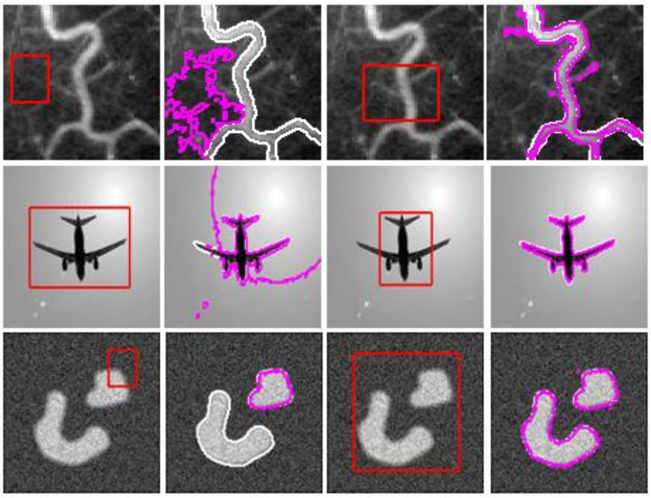

Figure 1 Dependency of Shi Model on curve initialization. From left to right columns – first and third: curve initialization in red; second and forth: results of segmentation in magenta and reference contours in white.

This paper tries to improve FTC model by focusing on initialization step and derives a benefit of Kernel Fuzzy C-Mean Clustering algorithm[8] to dominant the high dependency on curve initialization.

The rest of paper is organized as follows. Section II introduces KFCM clustering and FTC model. Section III proposed approach is described. Experimental results are presented in Section IV. Finally this paper concludes in section V.

Table 1 Problems of level set-based methods and corresponding proposed method to solve it

Problem	Proposed method
Fails in Ambiguous and discrete edges	Geodesic Active Contour [9]
Noise sensitivity	Active contours without edge [10]
Depending on curve initialization	Variational B-Spline Level set [11]
Re-initialization of sign distance function	Evolution without re-initialization [12]
Unsuccessful to find interior contour of an object	Variational B-Spline Level set [11] and Region-Scalable Fitting Energy[13]
Fails in inhomogeneous region	Region-Scalable Fitting Energy[13], Localizing Region-Based Active Contours[14]
Computational complexity	Fast Two-Cycle Algorithm With Smoothness Regularization[7]

II. BACKGROUND

This paper uses KFCM clustering and FTC model for image segmentation. So some basic information about KFCM clustering method and FTC Model (an efficient kind of curve evolution algorithm based on level set for image segmentation) is explained in the following.

A. KFCM Clustering

A Kernel-Based Fuzzy C-Means clustering(KFCM) algorithm has been proposed by Zhang et al [15, 16] with strong noise robustness. In fact, it is obtained just by replacing a new kernel-based metric in the original Euclidean norm metric of FCM.

The KFCM partitions a dataset $X = \{x_1, x_2, \dots, x_n\} \subset R^P$, where P the dimension, into c fuzzy subsets by minimizing the following objective function :

$$J_m(U,V) = \sum_{i=1}^{c}\sum_{k=1}^{n} u_{ik}^m \|\Phi(x_k) - \Phi(v_i)\|^2 \tag{1}$$

where c is the number of clusters and determined by a prior knowledge , i.e. c=4 for brain image; n is the number of data points; u_{ik} is the fuzzy membership of $x_k$in class i; m is a weighting exponent on each fuzzy membership and controls clustering fuzziness (usually $m = 2$); V is the set of cluster centers or prototypes $v_i \in R^P$;and Φ is an implicit nonlinear map. It's better to mention that u_{ik} is a member of [0,1] and must satisfy$\sum_{i=1}^{c} u_{ik} = 1$ and $0 < \sum_{k=1}^{n} u_{ik} < n$. In feature space, a kernel can be a function which is called K, where $K(x,y) = \langle\Phi(x), \Phi(y)\ \rangle$ and $\langle . \rangle$ is the inner product. So:

$$\begin{aligned}\|\Phi(x_k) - \Phi(v_i)\|^2 &= \left(\Phi(x_k) - \Phi(v_i)\right)^T\left(\Phi(x_k) - \Phi(v_i)\right) \\ &= \Phi(x_k)^T\Phi(x_k) - \Phi(v_i)^T\Phi(x_k) \\ &- \Phi(x_k)^T\Phi(v_i) + \Phi(v_i)^T\Phi(v_i) \\ &= K(x_k, x_k) + K(v_i, v_i) - 2K(x_k\ , v_i)\end{aligned} \tag{2}$$

There are some popular kernel functions in [17]. In this paper we use Gaussian Radial basis function (GRBF) kernel $K(x,y) = \exp(\frac{-\|x-y\|^2}{\sigma^2})$ where σ is the width parameter, then:

$$K(x,x) = 1 \tag{3}$$

By substituting Eq. (2) and Eq. (3) in Eq. (1), we have:

$$J_m(U,V) = 2\sum_{i=1}^{c}\sum_{k=1}^{n} u_{ik}^m[1 - K(x_k\ , v_i)] \tag{4}$$

Similar to FCM, the optimization problem comes to minimize $J_m(U,V)$ under the constraints of u_{ik}. Then:

$$u_{ik} = \frac{(1 - K(x_k, v_i))^{-1/(m-1)}}{\sum_{j=1}^{c}(1 - K(x_k, v_j))^{-1/(m-1)}} \tag{5}$$

, and:

$$v_i = \frac{\sum_{k=1}^{N} u_{ik}^m K(x_k, v_i) x_k}{\sum_{k=1}^{N} u_{ik}^m K(x_k, v_i)} \tag{6}$$

Summarization of KFCM algorithm is described in Table 2. In this algorithm, similarity measure in FCM, i.e. Euclidean norm metric, is replaced by a new kernel-induced metric (in this paper, Gaussian kernel) which makes the weighted sum of data points more robust. So this algorithm is a robust clustering approach if an appropriate value for sigma would be chosen. It's obtained by trial-and-error technique or experience or prior knowledge which neither too large nor too small. We consider 150 for sigma like [15] does.

As mentioned in [15], KFCM needs to be improved for image segmentation. This paper applies the power of curve evolution based on level set to increase the efficiency of segmentation by KFCM.

Table 2 Algorithm of KFCM clustering

I. Initialize c, t_{max}, m>1, $\varepsilon > 0$ for positive constants.
II. Initialize the membership matrix u_{ik}^0
III. For t=1 to t_{max} do:
   a) Update all prototype v_i^t with $v_i = \frac{\sum_{k=1}^{N} u_{ik}^m K(x_k, v_i) x_k}{\sum_{k=1}^{N} u_{ik}^m K(x_k, v_i)}$
   b) Update all memberships u_{ik}^t with $u_{ik} = \frac{(1-K(x_k, v_i))^{-1/(m-1)}}{\sum_{j=1}^{c}(1-K(x_k, v_j))^{-1/(m-1)}}$
   c) Compute $E^t = max_{i,k}\left|u_{ik}^t - u_{ik}^{t-1}\right|$, if $E^t \le \varepsilon$, stop;
   End;

B. Fast Two Cycle Model

Shi and Karl [14] approximates the level-set function in a narrow band using an integer valued array. They used a fast two-cycle (FTC) algorithm instead of solving Partial Differential Equations (PDEs) to speed up the computations. The basic idea is using of two cycle for curve evolution, one cycle for data-dependent term and another one for smoothness regularization. Implicit function is approximated by a piece wise constant function and defined by only four values for fast computation:

$$\phi(\mathrm{x}) = \begin{cases} 3 & \text{x is extrior point} \\ 1 & \mathrm{x} \in \mathrm{L_{out}} \\ -1 & \mathrm{x} \in \mathrm{L_{in}} \\ -3 & \text{x is interior poin} \end{cases} \tag{7}$$

Where

$$\begin{cases} L_{out} = \{x | x \in \Omega\ \ and\ \exists y \in N(x); y \in D\backslash\Omega\} \\ L_{in} = \{x | x \in D\backslash\Omega\ \ and\ \exists y \in N(x); y \in \Omega\} \\ \mathrm{N(x)} = \left\{ y \in D \middle| \sum_{k=1}^{K} |\mathrm{y_k} - \mathrm{x_k}| = 1 \right\} \end{cases}$$

Consider C is a curve which can evolve iteratively under a speed function and stop when it converges. The set of grid points enclosed by C as the object region Ω and the set of

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points $D\backslash\Omega$ as the background region. The interior points are those grid points inside C but not in L_{in} and similarly, the exterior points are those points outside C but not in L_{out}. This function approximates the signed distance function locally.

Their algorithm can apply some evolution speeds that composed of a data-dependent term and a curve smoothness regularization term. So the general speed function F is $F = F_{int} + F_d$.

In this paper we use speed function of CV model[9] for data-dependent speed, F_d :

$$F_d = H(\phi(x))(I(x) - v)^2 + (1 - H(\phi(x)))(I(x) - u)^2 \qquad (8)$$

Where I is the intensity, H is Heaviside function which is defined as $H(z) = \begin{cases} 1 & z \geq 0 \\ 0 & z < 0 \end{cases}$,

$$u = \frac{\int_\Omega \left(1 - H(\varphi(x))\right) . I(x) dx}{\int_\Omega \left(1 - H(\varphi(x))\right) dx}, \text{ and } v = \frac{\int_\Omega H(\varphi(x)) . I(x) dx}{\int_\Omega H(\varphi(x)) dx}.$$

Then they just use the sign of evolution speed function F.

So, $\widehat{F_d} = \begin{cases} 1 & F_d > 0 \\ 0 & F_d = 0 \\ -1 & F_d < 0 \end{cases}$

They use MBO algorithm [18, 19] for smoothing speed, F_{int}, which is derived Gaussian filtering:

$$\hat{F}_{int} = \begin{cases} 1 & for\ x \in L_{out}, if\ G \otimes H(-\phi)(x) > \frac{1}{2} \\ -1 & for\ x \in L_{in}, if\ G \otimes H(-\phi)(x) < \frac{1}{2} \\ 0 & otherwise \end{cases}$$

where $\otimes$ is the convolution operation.

This algorithm is fast enough to apply in real-time application. The cause is that the evolution steps use only integer operations in both cycles by two simple element switching mechanisms between two linked lists. They called these mechanisms, *switch_in* to move the boundary outward by one grid point at that location and similarly *switch_out* to move the boundary inward. The algorithms of Switching Mechanisms and FTC algorithm for image segmentation are represented in Table 3 and Table 4 respectively.

Table 3 Switch_in and Switch_out algorithms

Switch_in(x)

For a point $x \in L_{out}$
1. Delete x from L_{out}.
2. Add those N(x) which were exterior points to L_{out}.
3. Insert x to L_{in}.

Switch_out(x)

For a point $x \in L_{in}$
1. Delete x from L_{in}.
2. Add those N(x) which were interior points to L_{in}.
3. Insert x to L_{out}.

III. PRPOSED APPROACH

The efficiency of FTC model depends on curve initialization extremely. Because of curve evolves just in a narrow band of initial curve. This paper uses the KFCM clustering to improve and automate image segmentation.

The proposed approach consists of two successive stages to integrate FTC model with KFCM clustering for image segmentation. Firstly, the KFCM is used to extract ROI's fuzzy membership matrix. Secondly, zero level set is initialized using this matrix and curve would be evolved iteratively by FTC model to converge and segment the ROIs. It can be seen in Table 5 The algorithm of proposed method and in Figure 2 Framework of roposed approach.

Table 4 FTC Algorithm for image segmentation by curve evolution based on level set[14]

1. ***Initialize** following values:*
   a) ϕ, $\widehat{F_d}$ and $\hat{F}_{int}$ *based on initial curve*.
   b) t_{max} (predefined maximum iterations)
2. ***Cycle 1: data dependent evolution***
   For i=1 to N_a *do*
   a) *Compute* F_d *for each point in* L_{out} *and* L_{in} *and store its sign in* $\widehat{F_d}$*, so:*
      $\widehat{F_d} = \begin{cases} 1 & F > 0 \\ 0 & F = 0 \\ -1 & F < 0 \end{cases}$
   b) *Outward evolution:*
      For each point $x \in L_{out}$ *, if* $\widehat{F_d}$ *(x) > 0: switch_in(x).*
   c) *Eliminate redundant points in* L_{in}*.*
      For each point $x \in L_{in}$*, if* $\forall y \in N(x)$*,* $\varphi(y) < 0$*:*
      i. *Delete x from* L_{in}
      ii. *Set* $\varphi(x) = -3$*.*
   d) *Inward evolution. For each point* $x \in L_{in}$*, if* $\widehat{F_d}$ *(x) < 0: switch_out(x)*
   e) *Eliminate redundant points in* L_{out}*. For each point* $x \in L_{out}$*, if* $\forall y \in N(x)$*,* $\varphi(y) > 0$*,*
      i. *Delete x from* L_{out}
      ii. *Set* $\varphi(x) = 3$*.*
   f) *Check following stopping condition, if it is satisfied, go to 3; otherwise continue this cycle.*
      I. The speed at all the neighboring grid points satisfies:
      $\hat{F}(x) = \begin{cases} \leq 0 \ ; for\ all\ x \in L_{out} \\ \geq 0 \ ; for\ all\ x \in L_{out} \end{cases}$
      II. $T = t_{max}$
   End;
3. ***Cycle 2: smoothing via Gaussian filtering***
   For i=1 to N_s *do*
   a) *Compute the smoothing speed* $\hat{F}_{int}$ *for each point in* L_{out} *and* L_{in}*.*
   b) *Outward evolution. For each point* $x \in L_{out}$ *, if* $\hat{F}_{int}$ *(x) > 0: switch_in(x).*
   c) *Eliminate redundant points in* L_{in}*. For each point* $x \in L_{in}$*, if* $\forall y \in N(x)$*,* $\varphi(y) < 0$*:*
      i. *Delete x from* L_{in}
      ii. *Set* $\varphi(x) = -3$*.*
   d) *Inward evolution. For each point* $x \in L_{in}$*,) if* $\hat{F}_{int}$ *(x) < 0: switch_out(x).*
   e) *Eliminate redundant points in* L_{out}*t. For each point* $x \in L_{out}$*, if* $\forall y \in N(x)$*,* $\varphi(y) >$ *:*
      i. *Delete x from* L_{out}
      ii. *Set* $\varphi(x) = 3$*.*
   End;
4. *If **stopping condition** not satisfied in 2, go to 2.*

Figure 2 Framework of roposed approach

IV. EXPERIMENTAL RESULT

To evaluate proposed approach, the authors use different kinds of images including medical data imagery, natural scene and synthetic data. They simulated the proposed

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approach in Matlab 2008. The information of input images in Figure 3 are as follows: Vessel image borrowed from [12](first row); Brain image borrowed from [22](second row); Airplane image borrowed from [23](forth row); finally two object image borrowed from [2](last row).

Table 5 The algorithm of proposed method (KFCM+FTC)

1. Stage 1: the KFCM clustering *i. Set value of c, t_{max} (maximum iteration number), m=2, $\sigma = 150$, $\varepsilon = 0.001$.* *ii. Continue from step 2 in Table 2 which consists of KFCM algorithm* *iii. Extract ROI's fuzzy membership matrix.*
2. Stage 2: Curve evolution by Shi model *i. Initialize the zero level set using the output matrix of stage 1(part iii) with following function [20, 21] :* $\phi(x, y, t=0) = \begin{cases} 1 & inside\ ROI \\ 0 & outside\ ROI \end{cases}$ *ii. Continue from step 1 in Table 4 which consists of the algorithm of FTC Model* *End;*

In implementation of KFCM, the parameters *m* and σ are fixed for all input images while the number of clusters, parameter *c*, varies with respect to input image. It is determined based on prior knowledge of image. It was set value "3" for the images of vessel, bone, airplane and two objects; and value "4" for brain images in our simulation.

The algorithm of FTC model (Table 4) has four parameters, N_a, N_s, N_g and σ. N_a controls data-dependent speed and three other ones effects on smoothing regulation speed. Their experimental showed that their method is robust with respect to perturbation of these parameters [14]. So these parameters are generally chosen as follows: $N_a=30$, $N_s=3$, $N_g=3$ and $\sigma = 1$ similar to those they applied. The max iteration, t_{max}, was considered 200 as well.

Figure 3 shows the simulation result of proposed approach. From left to right, first column is original image, second column is the result of KFCM clustering, and the last one is the result of integrating KFCM with FTC model (proposed approach). The second column shows that the KFCM clustering can't operate well alone. Moreover FTC model is high dependent on initial curve as depicted on figure 1. The third column of figure 3 illustrates promising result of this integrating where ROIs boundaries, i.e. segmentation result is in red.

V. CONCLUSION

This paper derives the benefit of Curve evolution by FTC model and the KFCM clustering for image segmentation by integrating them. In fact, FTC model is so efficient in terms of computational complexity and accuracy among available image segmentation method based on curve evolution by level set. But it's dependent on curve initialization extremely. This paper uses fuzzy membership matrix of KFCM for initial curve to solve this problem. Simulation result shows promising outputs for segmentation of different kinds of image including medical data imagery, natural scene and synthetic data.

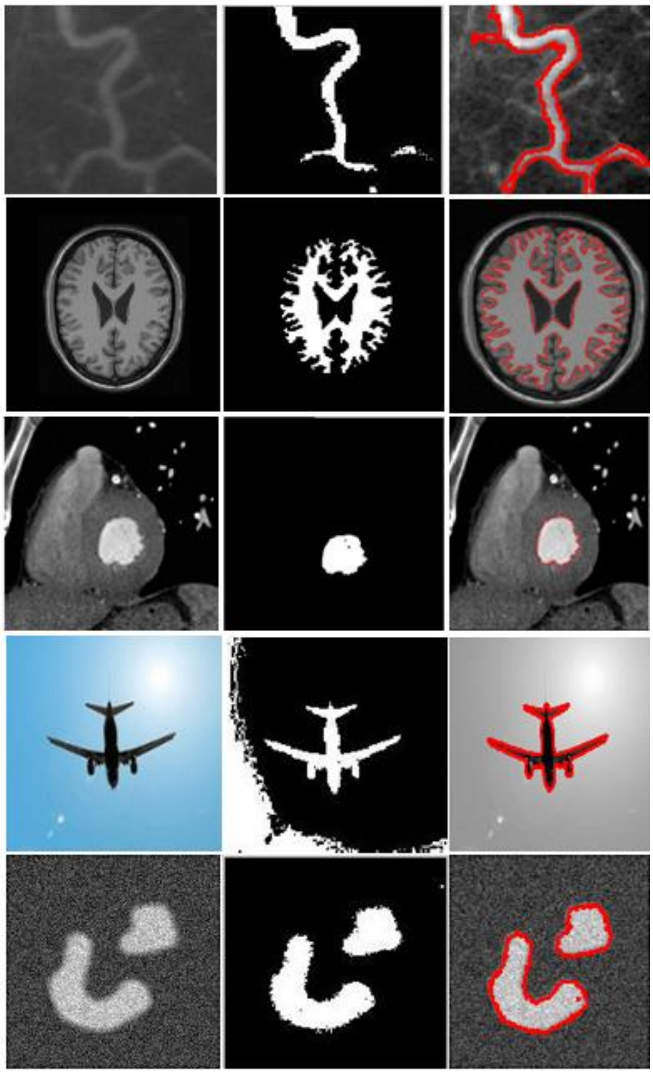

Figure3 Simulation result for different kinds of images, the columns from left to right: original image, result of KFCM, result of proposed approach in red.

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