A Hybrid Image Segmentation Model Based on GMM and CV Model

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Abstract. Traditional CV level set segmentation model is vulnerable to image noise and non-uniform gray level in the target area, which affects the segmentation accuracy. In this paper, we propose a new image segmentation model, which combines Gaussian mixture model (GMM) and CV level set image segmentation algorithm. We use the GMM foreground detection result as important prior information of CV level set image segmentation in order to integrate multi-information. We add different gray values to foreground area and background area to increase contrast. We put the new different gray values into the level set function to construct new energy terms and it effectively minimize inaccurate edge location caused by the image noise and uneven gray scale in image. In this paper, our method compares to LIF, LBF, RSF and other CV level set image segmentation algorithm, and the experiment result shows that our method is better than others and achieves faster convergence.

1. Introduction
In computer vision field, image segmentation is a useful method for digital image process. The result of image segmentation can be used to obtain the the information which exist in the interesting image region. The quality of image segmentation technology directly affects the subsequent image processing effect. However, it becomes more and more difficult for image to segment, because researchers can not deal with image noise properly, and other problems like blurred boundary features and uneven gray level. In order to overcome the above problems, many scholars have proposed methods, which can suppress noise, preserve image boundary to a certain extent, and then the experimental results were better than before [1].

Level set segmentation has many advantages: flexible topological transformation, smooth and continuous object boundary, strong mathematical theory support, and large amount of researchers applied the dynamic curve evolution of level set method for image segmentation, so the level set image segmentation algorithm has received more extensive attention and research. Some documents[2][3] show that the local information have contributed to satisfactory segmentation result. Some outstanding methods are as follows: Li proposed LBF(Local Binary Fitting)[3] to solve the uneven gray value problem, and this method make the best of local region information, thus it leads to complicated computation. To solve the problem of computational complexity and local region minimum, Zhang proposes LIF(Local Image Fitting) method [3], which effectively reduces the complexity and maintains the segmentation accuracy of uneven gray and noise images. However, there are still some problems in the segmentation of complex uneven gray images. Lin [4] proposes a RSF model for dynamic selection of local windows based on the change of gray level information of
images. However, this model uses edge detection function to measure the change of gray level information, so the image noise reduce the segmentation effect seriously. [5] proposes a new method which resolve the problem of salt and pepper noise image segmentation, but when the noise is strong, the segmentation accuracy is low or even fails. [6] proposes that local gray difference is helpful to solve the above problems. [6] algorithm makes use of different gray value under different noise conditions, and improves the anti-noise ability of image segmentation by adding noise repair function. Due to complexity, the algorithm is prone to islanding phenomenon of segmentation.

Although the above methods have achieved excellent results, the essence of these methods is to optimize local region model or weaken noise influence. Only taking into account local region information, the model may fall into local minimum, even failure to experiment. We consider that foreground region is target region, and the it must be deep contrast with backgroud region, and both of them can be put together, so we use GMM (Gaussian mixture model) foreground detection results are used as the prior information of CV level set image segmentation model, which achieves the goal of multi-information fusion and effectively solves the impact of noise and gray level inhomogeneity on image segmentation.

2. Related Work

2.1. Gaussian Mixture Model
At first, GMM and EM optimization process need to be introduced. We will represent all the pixel as \( \Omega = \{1,...,N\} \), and the features as \( \{x_1,...,x_N\} \). GMM means a model mixed some Gauss distribution. Supposing that GMM has \( k \) branches, and we can get the \( x_j \) from one of the Gauss distribution by random sampling. Let \( z_j \) be the \( x_j \) corresponding to Gauss distribution branch, and \( z_j \) is unpredictable. \( z_j \in \{1,...,k\} \) is latent. We suppose that \( \Pi = (\pi_1,...,\pi_k) \) is Gauss prior probability distribution, and \( \theta_i = \{\mu_i, \Sigma_i\} \) is \( i \) th Gauss ditribution parameter: mean direction and covariance matrix. We defined GMM probability dense function as follows: \( p(x|\Pi, \Theta) = \sum_{i=1}^{k} \pi_i p(x|\theta_i) \). To estimate GMM parameters \( \{\Pi, \Theta\} \), EM algorithm iterates over and over the following steps:

E-step: we have known \((\Theta^t, \Pi^t)\), and compute the posterior probability \( z^t_i = p(z_j = i | x_j, \Theta^t) \):

\[
z_j^t = \frac{\pi_j^t \cdot p(x_j | \theta^t_j)}{\sum_{m=1}^{k} \pi_m^t \cdot p(x_j | \theta_m^t)}, \quad j = 1,...,n, i = 1,...,K
\]  (1)

M-step: update parameters \((\Pi^t, \Theta^t) \rightarrow (\Pi^{t+1}, \Theta^{t+1})\):

\[
\pi_i^{t+1} = \frac{1}{N} \sum_{j=1}^{N} z_{ji}^t, \quad \mu_i^{t+1} = \frac{\sum_{j=1}^{N} z_{ji}^t \cdot x_j}{\sum_{j=1}^{N} z_{ji}^t}, \quad i = 1,...,K
\]  (2)

\[
\Sigma_i^{t+1} = \frac{\sum_{j=1}^{N} z_{ji}^t (x_j - \mu_i^{t+1})(x_j - \mu_i^{t+1})^T}{\sum_{j=1}^{N} z_{ji}^t}, \quad i = 1,...,K
\]  (3)
2.2. CV Level Set Model

CV model drives the curve to the optimal contour by curve driving force [7][8]. Because of the existence of curves, we can see that two parts of image, the inner part and the outer part, which are represented as $\Omega_a$ and $\Omega_b$ respectively. $\Omega$ represents the image, we can define the energy functional as follows:

$$F(c_1, c_2, C) = \mu \cdot \text{Length}(C) + \nu \cdot \text{Area}(\text{inside}(C)) +$$

$$\lambda_1 \int_{\Omega_a} (I(x, y) - c_1)^2 \, dxdy + \lambda_2 \int_{\Omega_b} (I(x, y) - c_2)^2 \, dxdy$$

(4)

where $C$ means optimal contour, $I$ is the original image, $\mu$ denotes the weight of the curve length, $\nu$ denotes the weight of the area included in the curve. $\lambda_1, \lambda_2$ represent the energy parameters of the inner and outer regions of the curve, respectively, $c_1, c_2$ mean the gray value of inner and outer regions, respectively. $\Phi$ denotes level set function, and it is introduced to represent the above energy functional, and the problem of solving the energy function can be mapped to the zero level set in high dimensional space. The Signed Distance Function is option of $(x, y)\Phi(x, y)$ which means level set function, and the expression as follow:

$$\Phi(x, y) = \begin{cases} 
  d, & (x, y) \in \Omega_o \\
  0, & (x, y) \in C \\
  -d, & (x, y) \in \Omega_b 
\end{cases}$$

(5)

where $d$ means distance from high dimensional spatial points to level set, and the distance is usually Euclidean. We get the energy function through Equation (5):

$$F(c_1, c_2, C) = \mu \int_{\Omega_o} H'(\phi) |\nabla \phi| \, dxdy + \nu \int_{\Omega_b} H(\phi) \, dxdy +$$

$$\lambda_1 \int_{\Omega} (I(x, y) - c_1)^2 H(\phi) \, dxdy + \lambda_2 \int_{\Omega} (I(x, y) - c_2)^2 (1 - H(\phi)) \, dxdy$$

(6)

where $H(\phi)$ represents Heaviside function, $H'(\phi)$ means 1-dimensional Dirac measure function [9][10], and the Heaviside function and the Dirac function show in Equation (7) and (8) respectively:

$$H(\phi) = \frac{1}{2} \left[ 1 + \frac{2}{\pi} \arctan(\frac{\phi}{\epsilon}) \right]$$

(7)

$$H'(\phi) = \frac{1}{\pi} \cdot \frac{\epsilon}{\epsilon^2 + \phi^2}$$

(8)

where $\epsilon$ is constant, we will assign value in experiment, and according to the variational principle, the partial differential equation of the energy function is deduced:

$$\frac{\partial \phi}{\partial t} = H'(\phi) \left[ \mu \text{div} \left( \frac{\nabla \phi}{|\nabla \phi|} \right) - \nu - \lambda_1 (I(x, y) - c_1)^2 + \lambda_2 (I(x, y) - c_2)^2 \right]$$

(9)

We can obtain optimal zero level set value through minimizing the formula (9). We can use iterative optimization to get the solution. In addition, the fitting center calculation parameters used in Formula (9) are the mean gray values of the pixels inside and outside the curve.

3. CV and GMM Mixture Model

This paper proposed a hybrid segmentation method GMMC_v based on GMM (Gauss mixture model) and CV level set image segmentation algorithm. Our method combines the regional statistical information with the set information of contours. The main idea is to divide the image into two parts: the target foreground and the background according to the GMM, and assign the two parts to two different gray values. We know that the location of the difference in gray values is the contour boundary of the target area, so that the curve can quickly evolve to the target boundary.
We assume that the gray value of the foreground target area is $\mu_1$ and that of the background area is $\mu_2$, and construct a new energy term is $E_\Omega(x) = \int_\Omega |\mu_1 - \mu_2|^2 |dx$. The new energy functional is obtained as follows:

$$F(c_1, c_2, C) = -\int_\Omega |\mu_1 - \mu_2|^2 |dx + \mu \int_\Omega |H'(\phi)| \nabla \phi |dxdy + \nu \int_\Omega H(\phi)dxdy + \lambda_1 \int_\Omega (I(x, y) - c_1)^2 H(\phi)dxdy + \lambda_2 \int_\Omega (I(x, y) - c_2)^2 (1 - H(\phi))dxdy$$

Due to the $E_\Omega(x)$, not only can avoid the model falling into the local minimum value. According to level set algorithmic thought, we added the evolution curve to the level set function, and obtained functional expression of level set evolution as follows:

$$E^{GMMC} (\phi, \mu_1, \mu_2) = \frac{1}{2}\int_\Omega [I(x) - I(x)]^2 |dx - \int_\Omega H_x(\phi(x))(1 - H_x(\phi(x))) |\mu_1 - \mu_2|^2 |dx$$

According to variational method and standard gradient downflow, the expression of level set evolution is obtained as follows:

$$\frac{\partial \phi}{\partial t} = \delta_x(\phi)((I - I)(\mu_1 - \mu_2) - (1 - H_x(\phi(x))) |\mu_1 - \mu_2|) + \nu \delta_x(\phi) \text{div} \left( \frac{\nabla \phi}{|\nabla \phi|} \right) + \mu (\nabla^2 \phi - \text{div} \left( \frac{\nabla \phi}{|\nabla \phi|} \right))$$

Where $H_x(\phi), \delta_x(\phi)$ represent Heaviside function formula (7) and 1-dimensional Dirac function formula (8).

4. Experiment

We experiment with different types of pictures and LBF, LIF, RSF and [6] methods based on CV level set model are compared. The dataset used in the experiment is BSDS 500 image segmentation dataset provided by Computer Vision Group of Berkeley University. There are 200 training pictures, 200 test pictures, 100 verification pictures and ground truth manual identification. Our experimental environment is as follows: Win7 64-bit operating system, Intel Core i5-3337U CPU 1.8GHz, 12GB Memory, and we use Matlab 2014a and opencv 3.1 as image processing tools.

4.1. Evaluation

In order to achieve quantitative evaluation of algorithm performance, we use the following four evaluation criteria. The expression are as follows:

$$TPR = \frac{|S_A \cap S_T|}{|S_T|}$$

$$FPR = \frac{|S_A \cap S_T - S_T|}{|S_T|}$$

$$SI = \frac{|S_A \cup S_T|}{|S_A 

\cup S_T|}$$

Where $S_T$ is truth target area of image, $S_A$ is experimental result area of image, and $SI$ means similarity between target region and experimental result region. Otherwise, RMSE (Root Mean Square Error) can be used as measurement of experimental result. The experimental result is expressed as $(x_i, y_i)(i = 1, 2, ..., n)$, and the ground truth coordinates is $(x'_i, y'_i)(i = 1, 2, ..., n)$.

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}[(x_i - x'_i)^2 + (y_i - y'_i)^2]}{n}}$$
4.2. Image Segmentation Result

![Figure 1](image.png)

**Figure 1.** The image segmentation result, (a) unprocessed image, (b) our method result, (c) LIF model result, (d) LBF model result.

We used a picture with a small contrast between the foreground and the background to test, and the result is shown in Figure 1. We found that due to low contrast of the test image, it was difficult for LIF and LBF model to distinguish the image edge, on the contrary, our method can accurately find the boundary of the target area. We use BSDS 500 datasets to test, and some experimental results are shown in Figure 2. We can get the result that our method is superior to other experimental methods from Figure 2.

The specific evaluation of the experimental results can be seen from Table 1. Accoring to the experimental results in Table 1, we find that the RMSE and FPR of our method are the lowest in their columns, and both of SI and TPR are highest. All in all, the method presented in this paper has achieved good experimental results.

| Method   | RMSE   | SI/%   | TPR/%  | FPR/%  |
|----------|--------|--------|--------|--------|
| Our method | 3.99   | 94.78  | 95.11  | 5.52   |
| LIF      | 8.73   | 90.09  | 89.26  | 11.37  |
| LFB      | 17.27  | 91.20  | 88.89  | 12.02  |
| RSF      | 9.91   | 84.28  | 74.37  | 15.61  |
| [6] method | 13.10  | 89.77  | 90.01  | 10.77  |

5. Conclusion

We propose a new mixture model combining GMM and CV model. According to the information inclusion of CV level set, we use GMM to detect the target area of the image, and assign different gray values to foreground area and background area. The gray values are used as the driving force of CV model curve evolution, and a new energy function is constructed to evolve the curve. Through comparative experiments, our method is better than other methods, but our method only considers the local information of the image foreground area. How to use the global information and construct a new energy term is the focus of the next work.

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Figure 2. Comparing results of various algorithms: (a) Unprocessed images, (b) Our method processed images, (c) LIF method processed images, (d) LBF method processed images, (e) RSF method processed images, (f) [6] method processed images.

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