An Improved Image Segmentation Algorithm Based on Local Gaussian Distribution Fitting Energy Model

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Abstract. The active contours driven by local Gaussian distribution fitting (LGDF) energy segmentation method can effectively handle brain tumors and other medical image segmentation. But this method needs a manual initial contour and is more sensitive to the position of the initial contour. It may fail to segment the target image when the initial contours are inappropriate. Therefore, an improved method based on LGDF model is proposed. It combines the unsupervised learning algorithm of K-means clustering algorithm with the LGDF segmentation algorithm. First the K-means clustering algorithm is used to get the primary segmentation and make it as the initial contour position of LGDF model instead of a manual one. Then the LGDF model is used for fine segmentation based on the coarse segmentation of clustering algorithm so as to get an accurate segmentation result. The experimental results show that the proposed method could obtain segmentation automatically rather than manually labeling of the initial contour, and satisfied results are obtained with less calculation time.

1. Introduction

Image segmentation is the key step in the image analysis and processing, and it is extremely important for research in the field of computer vision [1]. Currently, active-contour-model image segmentation methods have been extensively studied [2]. It can be divided into two kinds of models based on the edge [3] and regional [4] information respectively. However, to images with intensity inhomogeneity, such as the medical image, the most of the active contour models are not very ideal.

It is assumed that the image is piecewise constant value, and the famous piecewise constant (PC) model is proposed in [5]. Satisfactory results on an uniform gray image segmentation is achieved. On the basis of PC model, Vese [4] further assumed that the image is piecewise smooth and proposed piecewise smooth (PS) model, which, to a certain extent, enhances the ability of the model for image segmentation with intensity inhomogeneity. Based on local information of gray image, Li [6] proposed Local Binary Fitting (LBF) model, which achieved satisfactory results when dealing with images with Intensity inhomogeneity. Wang [7] further assumed that the local information of image is submitted to the Gaussian distribution, and proposed local Gaussian
distribution fitting (LGDF) model based on Bayesian classification criteria. This method firstly described the local gray information of image with Gaussian distribution, and then defined the local Gaussian fitting energy equation with maximum a posteriori. By integrating the LGDF energy equation, the global energy fitting equation was obtained. At last, energy equation was solved by the level set method. With the mean and variance of the Gaussian distribution as the spatial variable of the equation, this method got better robustness segmentation results of the images with intensity inhomogeneity.

However, this method also has shortcomings. By this method, you have to manually select the initial contour. And active contour model based on local information is more sensitive to the location of the initial contour. Different initial contours will lead to different, even wrong segmentation results. The different initial contours may also lead to the slow convergence and more iterations of the algorithm.

Here a novel method which incorporates K-means clustering with LGDF model is proposed to get a better segmentation. The K-means clustering is an unsupervised learning algorithm. The K-means clustering method is first used to produce a primary segmentation of the image automatically instead of a manually labelled initial contour. Then the coarse segmentation is applied to the LGDF segmentation algorithm. The LGDF method with the good primary segmentation also improves the accuracy of segmentation, which further decreases the iterations of the level set and reduces computational time.

2. Clustering and K-means clustering

Clustering analysis is an important technology in data mining, and it has been widely used in areas such as statistics, image processing, medical diagnosis, information retrieval, biology and machine learning [8]. Among the various clustering algorithm, the fuzzy C-means clustering algorithm (FCM) has been applied to image segmentation in a large range in medical field, such as MR images. But its computation is complex, and its performance will degrade obviously as the noise level is boosted, which are its main defects [9].

Furthermore, as a simple unsupervised learning clustering, the computation of K-means clustering algorithm [10] is low comparing to FCM. The clusters generated from K-means clustering do not overlap one another. Moreover, the quantity of clusters (K) is generally calculated from images of certain regions of human anatomy [11]. Thus, the method is suitable for the biomedical image segmentation.

K-means clustering [8] means that the dataset can be divided into K clusters. K in “K-means” particularly indicates the number of clusters as this algorithm is employed. These clusters are determined in accordance with the similarity criterion among the data points. The similarity criterion adopted by the K-means clustering algorithm is the minimization of SSE (sum of the squared error) criterion. The algorithm could make all of the data point get a minimum distance to the center of its own cluster. The SSE criterion function is defined as follows,
\[ \text{SSE} = \sum_{j=1}^{k} \sum_{i=1}^{n} \|x'_i - c_j\|^2 \]

Where \( \|x'_i - c_j\|^2 \) is a chosen distance measure between a data point \( x'_i \) and the cluster centre \( c_j \). Thus it is an indicator of the distance of the \( n \) data points from their respective cluster centers.

Implementation steps are as follows:

Step 1: Choose \( K \) points as the initial centers;

Step 2: Calculate the distances from each data point to the \( K \) points, find the minimum distance and assign each point to the nearest center from \( K \) clusters;

Step 3: Recalculate and reclassify each cluster center and modify the new center;

Step 4: End the algorithm until the cluster centers remain unchanged;

After the K-means clustering segmentation, we further implement the morphological image processing, which includes the connectivity processing [12]. In the 2-D binary image segmentation result of K-means clustering on the original image, 8-connected components are computed, and every object is assigned different labels. Then we can get the target area in the segmentation. By this process, small false target area caused by noise could be eliminated.

![Figure 1. Comparison of before and after connectivity processing.](image)

(a) K-means clustering segmentation  (b) Result after connectivity processing

3. LGDF model

The LGDF model is put forward by [7] to take full advantage of local information of the image. In LGDF, the local image intensities are described by Gaussian distributions with different means and variances. The data fitting energy function is defined as follows,

\[ E_{x}^{\text{LGDF}} = \sum_{i=1}^{2} \int_{V} -\rho(x - y) \log p_{i,x}(I(y)) dy \]

(2)
The contour is driven by this term towards the boundaries. In the formula, \(-\rho(x-y)\) is a non-negative weighting function chosen as a truncated Gaussian kernel with a localization property. \(p_{i,x}(I(y))\) is the probability density function of the number i district, which follows the following Gaussian distribution,

\[
p_{i,x}(I(y)) = \frac{1}{\sqrt{2\pi}\sigma_i(x)}\exp\left(-\frac{(u_i(x) - I(y))^2}{2\sigma_i^2(x)}\right)
\]

(3)

The length term could maintain smoothness of the evolution curve and avoid small isolated area in the final segmentation result. The energy punishment term could correct the deviation between the level set function and signed distance function in real time, which could avoid complex, time-consuming re-initialization and could ensure the stability of numerical calculation. The length term is given by

\[
\mathcal{L}(\phi) = \int_{\Omega} \delta(\phi(X))|\nabla \phi(X)|\,dx
\]

(4)

The energy punishment term is given by the following integral

\[
\mathcal{P}(\phi) = \int_{\Omega} \frac{1}{2}(|\nabla \phi(X) - 1|^2\,dx
\]

(5)

Then, the final whole energy function is as following,

\[
\mathcal{F}(\phi,u,\sigma^2) = \sum_{i=1}^{2} \int_{L_h} -\rho(x-y)\log p_{i,x}(I(y))\,dy + a\mathcal{L}(\phi) + b\mathcal{P}(\phi)
\]

(6)

Where a and b are non-negative constants.

4. Proposed algorithm procedure

The main idea of the proposed method is put forward based on the LGDF model image segmentation by combining K-means clustering. The target area is first obtained by adopting the K-means clustering segmentation curve after appropriate morphological operations. Then it is used as the initial contour curve of LGDF model algorithm for fine segmentation. This method not only avoids the error segmentation caused by incorrect manually-labelled initial contour, but also improves the speed of the curve evolution. Implementation steps are described as follows,

Step 1: Input an image and conduct the K-means clustering segmentation.

Step 2: Conduct the connectivity processing to eliminate small false target area caused by noise.

Step 3: Make the coarse segmentation of clustering as the initial contour of LGDF model, which is the initial value of the level set function in the LGDF model.
Step 4: Conduct the evolution of the level set function, i.e. updating the local means and local variances.

Step 5: Judge whether the level set function convergences or not; if not, return to Step 4 till the end.

5. Result and discussion

The testing environment is Pentium CPU 2.90 GHz, 2 GB RAM, Windows XP 32 bit, and Matlab 2010a. Three images are chosen to test the segmentation method and the corresponding results are given.

The pre-segmentation by K-means clustering and the result by connectivity processing are shown in Figure 1. It shows that the clustering contour is in accordance with visual target contour. Then this result is set as the initial contour of the LGDF model. Since the initial contour is similar to the real target contour, the algorithm overcomes the bad effects of LGDF segmentation model by manually selecting initial contour. Besides, it reduces the number of iterations of the level set function to a certain extent.

Figure 2 and Figure 3 give the two segmentations of different images. Figure 2 is an infrared image. Figure 3 is a medical image. In each figure, the initial contours are plotted on the images in the first row while the final contours plotted on the images in the second row. In each figure, the first three columns show the result of manually selected initial contour and each column has a different initial contour position. The last column is the segmentation conducted by the proposed method. Its initial contour is got by the K-means clustering algorithm and connectivity processing.

Table 1 and Table 2 are the comparison of iteration number and the computational time between the segmentation results of Figure 2 and Figure 3. In each table, “iteration” means the number of iterations in level set. “Time” means the segmentation time in every different condition.

From Figure 2-Figure 3 and the statistic results in the tables, we can see that the first column in each figure shows the appropriate manual initial contour position, and the segmentation result by LGDF is quite ideal. However, the evolution of the level set function takes much time. The second and third columns manifest the result of other initial contour position. It clearly demonstrates that the result is affected by the choice of the initial contour. From these three columns of Figure 2 and Figure 3, we could conclude that a suitable initial contour can lead to a quality result, but an unsuitable one will affect the result and even bring about the failure of the segmentation. In the last column, the segmentation from the initial contour by K-means clustering processing is very ideal. Besides, iteration of the level set is cut down and the calculation process is reduced in comparison with the previous three results.
Figure 2. The segmentation results of infrared image. The first three columns give the initial contour and the final segmentation result of the traditional LGDF model with different initial contours. The last column gives the initial contour and the final segmentation result of the proposed method.

Table 1. Comparison of segmentation results of Fig.2.

<table>
<thead>
<tr>
<th>Method</th>
<th>Iteration</th>
<th>Time[s]</th>
</tr>
</thead>
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<tr>
<td>LGDF model</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fig2(a)</td>
<td>300</td>
<td>4.264446</td>
</tr>
<tr>
<td>Fig2(b)</td>
<td>600</td>
<td>8.483167</td>
</tr>
<tr>
<td>Fig2(c)</td>
<td>800</td>
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<tr>
<td>Proposed</td>
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<tr>
<td>Fig2(d)</td>
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Table 2. Comparison of segmentation results of Fig.3.

<table>
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<tr>
<th>Method</th>
<th>Iteration</th>
<th>Time[s]</th>
</tr>
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<tbody>
<tr>
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<td>Fig4(a)</td>
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<tr>
<td></td>
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<td></td>
<td>Fig4(c)</td>
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<td>Proposed</td>
<td>Fig4(d)</td>
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</tbody>
</table>

6. Conclusions

In order to avoid the weakness of the LGDF model, which involves sensitivity to initial contour and too much computational expense, a methodology combining the K-means clustering algorithm with the local Gaussian distribution fitting energy segmentation algorithm is put forward. It has been proved by the experimental results that it is of great effect to get initial image segmentation with the application of K-means clustering before employing the local Gaussian distribution fitting energy segmentation algorithm, which greatly improve the segmentation result and reduce the computational expense.

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References


