An Integrated Algorithm of Spatial Fuzzy C-Means Clustering and Level Set for Indoor Scene Image Segmentation

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Abstract—Traditional fuzzy clustering algorithm is applicable for noiseless image segmentation. However, it is powerless for the images with noise, special point values and defects. An algorithm which combines spatial fuzzy clustering and level set for indoor scene segmentation is proposed in this paper. Firstly, the image is classified using fuzzy clustering with space information to get a larger difference in image gray level; secondly, the image is segmented using level set; finally, the contour in the boundary of target area is gotten accurately. The improved method can not only preserve details of images but also reduce the number of iterations. The results show that the proposed method has good segmentation quality and efficiency in segmentation for indoor scene image.

Index Terms—spatial fuzzy c-means cluster; level set; indoor scene; image segmentation; fusion

I. INTRODUCTION

Indoor scene image understanding plays an important role in intelligent engineering especially for mobile robot to perform a specific task. However, the segmentation of indoor scene image is the first and significant step of indoor scene understanding. Image segmentation technology separates the target area which people interested in and prepares for the subsequent feature extraction, pattern recognition, and so on. The existing segmentation error may lead to the failure of high-level image processing, so the accuracy and the speed of segmentation are regarded as a bottleneck in the development of computer vision.

It is very difficult to segment indoor scene images accurately because of their unique complexity. Researches were done much in this area. Edge detection [1-3] and region segmentation [4] are two types of image segmentation methods. In image segmentation, gray differential is a basis for edge detection, such as gradient operator, Sobel operator, LoG operator, Roberts operator and Canny operator [5,6], and so on. In region segmentation, image is separated into K connectivity domains based on the consistency in internal region and the differences between various regions. These techniques include: threshold segmentation, regional growth, regional separation and mergers [7]. These methods achieved certain effects, but as for segmentation of image with more speckle noise, they often failed to get satisfactory results because of their poor anti-noise ability.

In recent years, scholars did further researches on image segmentation employed artificial neural network (ANN), wavelet transform, fuzzy clustering, genetic algorithms, mathematical morphology and other new theories and techniques[8-11], furthermore, good segmentation results were obtained by combining the foregoing segmentation methods. However, there is still not a complete theoretical system in image segmentation and the segmentation results also need to be improved.

Characteristic space of image was divided into a plurality of clusters according to the similarity degree of similar data by fuzzy clustering algorithm. The same cluster has the maximum similarity of data points while the different clusters have the minimum similarity. Data points of the classification cluster were determined according to the minimum distance between the pixel point and the clusters central point which were obtained by iterative calculation. More and more improved fuzzy clustering algorithm promoted the development of image segmentation[12,13]. Level set was a method for target detection of the image evolved by the curve using active contour model. A new algorithm is proposed in this paper...
which integrated the improved space fuzzy c-means clustering algorithm (SFICM) and the level set, combining the advantages of these two algorithms for indoor scene image segmentation.

The rest of the paper is organized as follows. In Section II, the principles of the SFCMLS algorithm were explained including fuzzy c-means clustering with special information, level set, the fusion of these two algorithms and the specific computational steps. In Section III, four groups of experiments were carried out from different perspectives using the algorithm. The corresponding results were presented and discussed in details. In Section IV, a conclusion was made about the algorithm of SFCMLS.

II. ALGORITHM
A. Space Fuzzy C-means Clustering Algorithm (SFCM)
In the FCM algorithm, suppose the image \( X = x_1, x_2, \cdots, x_n \) is divided into a number of c-means clusters according to the pixel values. The value function CF is defined as follows:

\[
CF = \sum_{j=1}^{n} \sum_{m=1}^{C} u_{mj}^m \left| x_j - v_j \right|^p
\]

(1)

Here, \( x_j \) is the gray value of the \( j \)th pixel, \( v_j \) is the value of the cluster center, \( u_{mj} \) represents the degree of membership which pixel \( x_j \) belongs to the \( m \)th cluster, \( m \) represents the fuzzy weighting exponent. In FCM algorithm, it completely depends on the distance between the target pixel of characteristic domain and the cluster center point. Membership function and the cluster center point were improved as follows:

\[
u_{mj} = 1 / \sum_{k=1}^{Q} \left( \left| x_j - v_i \right| / \left| x_j - v_k \right| \right)^{2(m-1)}
\]

(2)

\[
v_j = \sum_{j=1}^{N} u_{mj}^m x_j / \sum_{j=1}^{N} u_{mj}^m
\]

(3)

First, a number of points were selected randomly as the initial cluster center, when the local minimum of \( v_j \) or a saddle point of the value function was obtained by comparing membership function values in the iteration, the iteration was ended.

Traditional FCM method has disadvantages such as sensitive to noise and easy to fall into local minimum value. To reduce these problems, spatial information was considered in the following algorithm.

Neighboring pixels of an image often have high correlation, that is, neighboring pixels have similar attribute values, which indicate that these pixels most likely belong to a same cluster. Ahmed[14] proposed a method by modifying the objective function of the standard fuzzy c-means to reduce the influence of noise. Based on this, Keh-Shih Chuang[15] proposed a modified fuzzy c-means clustering method with incorporating spatial information into the membership function.

To make good use of the spatial information in an image for segmentation, the spatial function is defined as follows:

\[
h_{pj} = \sum_{k \in NB(x_j)} u_{jk}
\]

(4)

\( NB(x_j) \) represents a square area with pixel \( x_j \) as the center of the spatial domain, here a 5x5 square area is used in this paper. Similar to the membership function, spatial function \( h_{pj} \) represents the membership which the pixel \( x_j \) belongs to the \( i \)th cluster center. The value of spatial functions is larger when the pixels around a certain point belong to the same cluster. The equation combining the membership function and spatial function is shown as following:

\[
u_{mj}' = u_{mj}^m h_{pj}^m / \sum_{k=1}^{Q} u_{mk}^m h_{pk}^m
\]

(5)

\( p \) and \( q \) are two important parameters in the function. In a cluster domain, spatial function simply enhances the original membership while the clustering results remain the same. However, equation (5) can reduce the weight of noise pixel by highlighting its adjacent pixels. Therefore, it is easy to rectify the pixels in noise area or points misclassified of defective area.

Two clustering processes are required in each iteration step. The first clustering process is calculating membership function values in the spectral domain, which is as same as the traditional FCM algorithm. The membership information of each pixel is mapped to the spatial domain in the second process to calculate the value of spatial function. Therefore, a new degree of membership embedded in the spatial information function is calculated by the improved FCM algorithm. The iteration of FCM is terminated if the function value change of the clusters center is smaller than a certain threshold after two iterations. Consequently local minimum is avoided in the iterative process. After the clustering center is determined, each pixel is classified to the cluster with the maximum degree of membership by using fuzzy clustering method.

B. Level Set
Level set was proposed by Osher and Sethian[16] in 1988. It is to get a robust segmentation based on active contour model integrated adaptive regions information. The main idea of level set is to express implicitly the planar closed curve as higher dimensional level set function, and calculate the geometry features and movement through the level set function mentioned above. The method can utilize area and boundary information synthetically to segment image effectively. The sharp corner can be processed using level set for image segmentation, and the topology structure can be changed, what’s more, the boundary of complex objects can be segmented. Therefore, the method has obvious advantages in processing images with a complicated shape.
Given \( \phi(x, y, t) \) as a continuous level set function, closed curves \( C(p, t) \) as the zero level set curve corresponding to \( t \) moment, there is equation (6):

\[
\begin{align*}
C(p, t) &= \{(x, y) | \phi(x, y, t) = 0\} \\
C(p, 0) &= \{(x, y) | \phi(x, y, 0) = 0\}
\end{align*}
\]

Assume that \( \phi(x, y, 0) = \pm d \), the parameter \( d \) is the signed distance from pixel \((x, y)\) to the curve \( C(p, 0) \). It is defined that if the point \((x, y)\) is on the closed curve \( C(p, 0) \), then \( d \) is 0; while point \((x, y)\) is inside the curve, \( d \) is positive; otherwise \( d \) is negative. Therefore, if curve \( C(p, 0) \) is the zero level set function \( \phi(x, y, t) \) in any condition, then:

\[
\phi(C(t), t) = 0
\]

The perfect differential of equation (7) is

\[
\frac{d\phi}{dt} + \nabla \phi \cdot \frac{\partial \phi}{\partial t} = 0
\]

The inward unit normal vector of level set curve is:

\[
N = -\frac{\nabla \phi}{|\nabla \phi|}
\]

Assuming \( F \) represents the speed of outer normal direction, there is:

\[
\frac{\partial C}{\partial t} \cdot N = f
\]

Then equation (8) can be rewritten as:

\[
\frac{\partial \phi}{\partial t} = F |\nabla \phi|
\]

The expression of curvature \( k \) is obtained by calculating quadratic differential of arc length according to level set function \( \phi \):

\[
k = \nabla \cdot \frac{\nabla \phi}{|\nabla \phi|} = \frac{\phi_x \phi_y^2 - 2 \phi_x \phi_y \phi_y + \phi_y \phi_y^2}{(\phi_x^2 + \phi_y^2)^{3/2}}
\]

The moving direction of the curve varies according to different curvature: some extend outside while the others extend inward. If \( F \) satisfies the smooth conditions that \( \phi(x, y, t) \) can be maintained as a valid function, the evolution curve \( C \) can split and merge various topology changes with the evolution of \( \phi \).

C. Fusion of SFCM and Level Set

Given the original image \( u(x, y) \) is divided into two target regions \( \Omega_{in} \) and \( \Omega_{out} \) by active contour \( C \), and the average gray level of each region is \( C_{in} \) and \( C_{out} \). The energy functional is established as following according to spatial fuzzy clustering algorithm embedded curve \( C \):

\[
F(C) = F_{in}(C) + F_{out}(C) = \int_{\Omega_{in}} |u - C_{in}|^2 \, dx \, dy + \int_{\Omega_{out}} |u - C_{out}|^2 \, dx \, dy
\]

It can be seen that \( F(C) \) reaches a minimum when closed active contour \( C \) lies in the boundary \( C_0 \) of the two homogeneous regions. In order to regularize the level set curve, the energy function for image segmentation is obtained by adding regular items as curve length, area inward curve etc. it is as following:

\[
F(\phi, C_{in}, C_{out}) = \mu \int_{\Omega_{in}} \delta(\phi) |\nabla \phi| \, dx \, dy + \nu \int_{\Omega_{out}} H(\phi) \, dx \, dy + \lambda_1 \int_{\Omega_{in}} |u - C_{in}|^2 \, H(\phi) \, dx \, dy + \lambda_2 \int_{\Omega_{out}} |u - C_{out}|^2 (1 - H(\phi)) \, dx \, dy
\]

Here, \( \Omega \) is the definition domain of the entire image, the first item is the length of closed contour line \( C \), the second item is the internal area of \( C \), \( \mu, \lambda_1, \lambda_2, \nu \geq 0 \) is the weight coefficient of each energy item. The position of segmentation contour line \( C \), unknown \( C_{in} \) and \( C_{out} \) can be obtained eventually.

\[
C_{in} = \frac{\int_{\Omega} u(x, y) H_{r}(\phi) \, dx \, dy}{\int_{\Omega} H_{r}(\phi) \, dx \, dy}, \quad C_{out} = \frac{\int_{\Omega} u(x, y)(1 - H_{r}(\phi)) \, dx \, dy}{\int_{\Omega} (1 - H_{r}(\phi)) \, dx \, dy}
\]

D. Specific Algorithm Steps

Step 1: Input indoor scene image and filtered with 5*5 wiener;
Step 2: Determine the classification number and the weighted index;
Step 3: Calculate the neighborhood information value of each pixel using (4);
Step 4: Calculate \( u_i^t \) with spatial information using (5), substitute \( u_i^t \) into (3), \( v_j^t \) will be obtained;
Step 5: If the algorithm result is not convergence, takes the membership degree and the clustering center as the initial result, and go to step 3.
Step 6: Initial indoor scene image into two parts according to the result of step 5, one of the symbolic distance function is initialized to 1, and the other is initialized to -1, and set the initial parameter values;
Step 7: Calculate \( C_{in} \) and \( C_{out} \) using (15);
Step 8: Evolution the level set function using (14).
Step 9: Iteration if the result is not convergence and go to step 6, otherwise stop the iteration and get the contour.

III. RESULTS AND ANALYSIS

The experiment is carried out on a computer with the CPU of Intel (R) Pentium (R) @ 2.60 GHz, 2.0 GB memory, MATLAB R2012b as programming
The indoor scene images were segmented respectively. Objects were chosen on the principle from simple to complex which often used commonly in indoor scene such as chair, cup, desk, flower, computer table and sitting room.

The experiment is divided into four groups. The first group is compared with different methods of images segmentation such as Otsu and FCM. The second group is images segmented using the SFCMLS proposed in this article with different iterations. The third group is about sitting room image segmented in 3-cluster using SFCMLS. The fourth group is indoor scene image segmented using different parameters.

Fig.1 shows the segmentation results using different methods. The first column are the original indoor scene images, the second column are images segmented by Otsu, the third column are images segmented by FCM, the fourth column are images segmented by SFCMLS. The used segmentation threshold level and iteration number is shown in Table 1.

<table>
<thead>
<tr>
<th>Index</th>
<th>Name</th>
<th>Otsu level</th>
<th>Fcm level</th>
<th>Sfcmls iterations</th>
</tr>
</thead>
<tbody>
<tr>
<td>A10</td>
<td>chair</td>
<td>0.545098</td>
<td>0.44598</td>
<td>700</td>
</tr>
<tr>
<td>B10</td>
<td>cup</td>
<td>0.725490</td>
<td>0.785141</td>
<td>700</td>
</tr>
<tr>
<td>C10</td>
<td>desk</td>
<td>0.686275</td>
<td>0.834764</td>
<td>700</td>
</tr>
<tr>
<td>D10</td>
<td>flower</td>
<td>0.643137</td>
<td>0.743137</td>
<td>700</td>
</tr>
<tr>
<td>E10</td>
<td>Computer table1</td>
<td>0.611765</td>
<td>0.786275</td>
<td>700</td>
</tr>
<tr>
<td>F10</td>
<td>Computer table2</td>
<td>0.662745</td>
<td>0.790196</td>
<td>700</td>
</tr>
<tr>
<td>G10</td>
<td>Sitting room</td>
<td>0.529412</td>
<td>0.417647</td>
<td>700</td>
</tr>
</tbody>
</table>

It can be seen that Otsu method is sensitive to noise and target size, images with unimodal interclass variance have good segmentation in A10, B10 and C10, not good in D10, E10 and F10. FCM method has good performance, but it is sensitive to initial parameters and time-consuming. However, SFCMLS method has not only good performance but also high efficiency, especially in a bit complex indoor scenes.

Fig.2 shows the results of indoor scene images segmentation using SFCMLS proposed in this paper. The parameters used in the experiment in Fig.2 are $\mu=0.1$, $\lambda=2$, $\tau=1$, $\nu=-1$. The magenta line represents the initial while the green line represents the final results after iterations. The first column is the original images; the second column is the results after 100 iterations; the third column is the results after 500 iterations; the fourth column is the results after 1000 iterations; the fifth column is the results after 2000 iterations. Taking G20 as example, to get G21 it took about 7.964 seconds, to get G22 it took about 38.392 seconds, to get G23 it took about 76.835 seconds, to get G24 it took about 154.279 seconds.

We can see that the more the number of iterations, the higher the segmentation accuracy, but the operation time is longer. However, there is very little difference after 500 iterations. So it should be chosen a suitable iteration number in practical application.
Figure 2. Indoor scene images segmented using SFCMLS with different iterations

Fig. 3 shows the sitting room image segmented in 3-cluster by the SFCMLS method with 100 iterations. The magenta line represents the initial while the green line represents the final results after iterations. G30 is the original sitting room image, and the rest of 3 images are the segmentation results. The iteration time is 8.696889 seconds, 8.555509 seconds and 8.969633 seconds respectively. G31 has the best segmentation result while G32 and G33 can only reflect partial information with about the same time. Therefore, the choice of clustering is very important. However, in this paper the cluster is chosen manually.

Figure 3. Sitting room image segmented with 3-cluster using SFCMLS

In Fig. 4, G41 to G49 are the sitting room segmentation results with the fuzzy threshold changed from 0.1 to 1 with the step of 0.1, 100 iterations. The results show that with the threshold increasing, the zero level set goes farther away from the actual line and the independent block becomes adhesion.

Figure 4. Sitting room image segmented with different fuzzy threshold using SFCMLS

Fig. 5 shows that the iteration time elapses from the longest on threshold 0.1 with time 9.910118 down to the shortest on threshold 0.4 with time 7.759954 and then goes up on threshold 0.5 subsequently down, which presents a double-dip. However, the initial contour becomes smaller and smaller with the bigger fuzzy threshold and there is no contour when the threshold is 1. So the fuzzy threshold must be set less than 1.

Figure 5. The change of various values with different fuzzy threshold

Fig. 6 shows the indoor scene image segmentation using SFCMLS with different $\varepsilon$ (Dirac regulator). G61 to G65 are segmented with $\varepsilon$ changed from 0.5 to 2.5 with the step of 0.5, 100 iterations. It has no influence on initial curve, but can impact the evolution of the segmentation curve, the segmentation result is bad with $\varepsilon$ of 0.5, can not correctly distinguish between boundary points, and the time is 10.057 seconds. The segmentation result is better with the parameter $\varepsilon$ of 1.5 and time is 8.853 seconds. The time is 143.208 seconds with the $\varepsilon$ of 1.5.

However, with the increase of $\varepsilon$ values the segmentation result is not better while the time grow faster. So parameter $\varepsilon$ can be chosen as 1.5.

IV CONCLUSIONS

Fuzzy clustering and level set are two important methods of image segmentation. In fuzzy clustering, a new level set function is constructed using membership functions embedded spatial information, and a variational
level set energy functional model is established. In the paper these two kinds of ways are fused together effectively. Target object is extracted by minimizing the energy functional with the variational method. The model combines advantages of each method with advantages such as automatic topology changes, insensitive to the initialization, etc. It can get a good evolution of the efficiency and the high quality of image segmentation, improves the robustness and accuracy of the algorithm. So it suits for indoor scene image segmentation.

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