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Image segmentation with complicated background by using seeded region growing

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ABSTRACT

This study proposes a novel seeded region growing based image segmentation method for complicated background in both color and gray level images. The proposed fuzzy edge detection method, that only detects the connected edge, is used with fuzzy image pixel similarity to automatically select the initial seeds not in the detail and complicated background. The fuzzy distance is used to determine the difference between the pixel and region in the consequent region growing and the difference between two regions in the region merging. The conventional region growing is modified in this study to ensure that the pixel on the edge is processed later than other pixels. Finally, the simulations in study prove that the proposed method is better than other existing segmentation methods.

1. Introduction

Image segmentation is an important technique in the image pre-processing for extracting the interesting object from the background. The existing image segmentation techniques can be classified into the following approaches, thresholding techniques, boundary-based techniques, region-based techniques, clustering-based techniques and hybrid techniques [1–4]. Seeded region growing (SRG) is one of the hybrid methods [1], which starts with assigned seeds and grows regions by merging a pixel into the most similar neighboring seeded region. SRG is robust to the large variety of images because the characteristics of rapid and free to tune the parameters, and the considering of local information including regions similarity, boundaries and smoothness. However, the selection of the initial seeds influences the segmentation results very much. How to assign the initial seeds is a major topic in SRG. The authors in [2,3] assign the pixels between the edge regions to be the initial seeds. The similarity in the local region was also used to select the initial seeds automatically [4]. To avoid the initial seeds appearing in the detail and complicated background, the authors in [5] applied color quantization to the image in advance and then used a smoothness measurement, *J* value, to determine the initial seeds. Nevertheless, the unfavorable quantization leads to the poor segmentation results since the color quantization is a random process. This study proposes a fuzzy theory [6] based method, that is modified from the fuzzy edge detection method proposed in our previous research [7], to detect the connected edge, fuzzy similarity and fuzzy distance in SRG. In the proposed method, the initial seeds are selected and not in the detail and complicated background. This study furthermore modifies the conventional region growing to ensure that the pixel in the detail is processed later than other pixels. Hence this study based on segmentation methods can obtain better image segmentation ability than the existing SRG.

This study is organized as follows: Section 2 introduces the color space used in this study. Section 3 modifies the edge detection method from our previous research [7] to detect the connected edge. Section 4 introduces the proposed SRG based image segmentation method. The simulations results are presented in Section 5. Finally, a brief conclusion is given in Section 6.

2. YC_bC_r color space

In this study, YC_bC_r color space is used since the color difference of human perception can be directly expressed by Euclidean distance in YC_bC_r color space [4]. Therefore, the color image needs to be transformed from RGB color space to YC_bC_r space and each component of any pixel is normalized into $[0, 1]$. Significantly, the pixel located at position (i, j) in the image is denoted as a vector $\mathbf{x}_{i,j} = [R_{i,j}, G_{i,j}, B_{i,j}]^T$ for a color image or as a scale $x_{i,j} = Y_{i,j}$ for a gray level image. Where $R_{i,j}$, $G_{i,j}$ and $B_{i,j}$ are three components in RGB color space of the pixel located at position (i, j). The transformation

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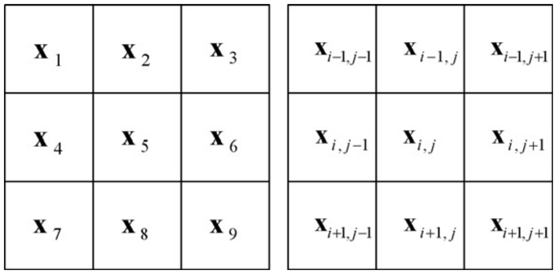

Fig. 1. The 3×3 sliding window with the center $\mathbf{x}_{j,i}$ and its neighboring pixels.

from RGB to YC_bC_r is shown as (1),

$$\begin{bmatrix} Y_{i,j} \\ Cb_{i,j} \\ Cr_{i,j} \end{bmatrix} = \begin{bmatrix} 65.481 & 128.553 & 24.966 \\ -39.797 & -74.203 & 112 \\ 112 & -93.786 & -18.214 \end{bmatrix} \times \begin{bmatrix} R_{i,j} \\ G_{i,j} \\ B_{i,j} \end{bmatrix} + \begin{bmatrix} 16 \\ 128 \\ 128 \end{bmatrix}. \tag{1}$$

After transforming the color space, the pixel located at position (i,j) in the color image is denoted as a vector $\mathbf{x}_{i,j} = [Y_{i,j}, Cb_{i,j}, Cr_{i,j}]^T$. To simplify the representation of this study, only the equations with vector forms are listed.

3. Connected edge detection

Consider a 3×3 sliding window whose center is the current pixel $\mathbf{x}_{i,j}$, the pixels in the sliding window are represented as $\mathbf{x}_n$, $n = 1, 2, \ldots, 9$ and shown in Fig. 1. An edge usually occurs in one of four possible patterns shown in Fig. 2. In the edge pattern of direction-1, nine pixels can be divided into two sets, S_0 and S_1 as $S_0 = \{\mathbf{x}_1, \mathbf{x}_2, \mathbf{x}_4, \mathbf{x}_5, \mathbf{x}_7, \mathbf{x}_8\}$ and $S_1 = \{\mathbf{x}_3, \mathbf{x}_6, \mathbf{x}_9\}$. Similarly, $S_0 = \{\mathbf{x}_1, \mathbf{x}_2, \mathbf{x}_3, \mathbf{x}_4, \mathbf{x}_5, \mathbf{x}_6\}$ and $S_1 = \{\mathbf{x}_7, \mathbf{x}_8, \mathbf{x}_9\}$ for the edge of direction-2, $S_0 = \{\mathbf{x}_1, \mathbf{x}_2, \mathbf{x}_3, \mathbf{x}_5, \mathbf{x}_6, \mathbf{x}_9\}$ and $S_1 = \{\mathbf{x}_4, \mathbf{x}_7, \mathbf{x}_8\}$ for the edge of direction-3, and $S_0 = \{\mathbf{x}_1, \mathbf{x}_2, \mathbf{x}_3, \mathbf{x}_4, \mathbf{x}_5, \mathbf{x}_7\}$ and $S_1 = \{\mathbf{x}_6, \mathbf{x}_8, \mathbf{x}_9\}$ for

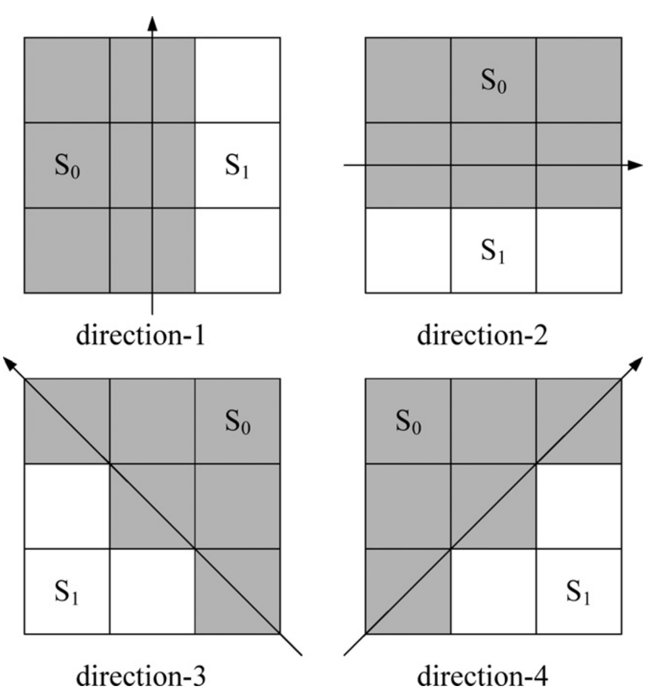

Fig. 2. Four possible edge patterns of different edge directions.

the edge of direction-4. Then, the fuzzy distance $d_s^{(k)}$ between S_0 and S_1 for direction-k are respectively defined as (2),

$$d_s^{(k)} = \min\left(\frac{\|\mathbf{m}_0 - \mathbf{m}_1\|}{w_d}, 1\right), \quad k = 1, 2, 3, 4 \tag{2}$$

where $\mathbf{m}_0$ and $\mathbf{m}_1$ are the vector means of the pixels in S_0 and S_1, respectively. w_d is a pre-defined parameter of the fuzzy distance which affects the slop of the fuzzy membership function. The smaller w_d that user selected, the more numbers of edge with small variation of color value will be detected. In this study, w_d can be set to 0.4. For the current pixel, (3) and (4) are used to record the maximal edge intensity $E_{i,j}$, which is the fuzzy membership degree of "the current pixel is an edge" and the corresponding edge direction $D_{i,j}$.

$$E_{i,j} = \max_{k \in \{1,2,3,4\}} (d_s^{(k)}), \tag{3}$$

$$D_{i,j} = \mathrm{Arg}\left(\max_{k \in \{1,2,3,4\}} (d_s^{(k)})\right). \tag{4}$$

After all pixels in the image are processed by the above procedures, the edge map E and direction map D of the entire image are generated. Since the edge intensity and the edge direction of the pixel are obtained, the following criteria can be used to determine the fuzzy membership degree $CE_{i,j}$, that is "the current pixel is a connected edge" of each pixel.

$$\text{If } D_{i,j} = 1, \text{ then } CE_{i,j} = \frac{1}{3}(E_{i-1,j} + E_{i,j} + E_{i+1,j}). \tag{5a}$$

$$\text{If } D_{i,j} = 2, \text{ then } CE_{i,j} = \frac{1}{3}(E_{i,j-1} + E_{i,j} + E_{i,j+1}). \tag{5b}$$

$$\text{If } D_{i,j} = 3, \text{ then } CE_{i,j} = \frac{1}{3}(E_{i-1,j-1} + E_{i,j} + E_{i+1,j+1}). \tag{5c}$$

$$\text{If } D_{i,j} = 4, \text{ then } CE_{i,j} = \frac{1}{3}(E_{i+1,j-1} + E_{i,j} + E_{i-1,j+1}). \tag{5d}$$

In the end of edge detection, define a fuzzy membership degree of "the current pixel is not a connected edge" $NCE_{i,j}$,

$$NCE_{i,j} = 1 - CE_{i,j}. \tag{6}$$

Both fuzzy membership degrees $CE_{i,j}$ and $NCE_{i,j}$ of each pixel must be recorded since they will be used in the following SRG.

4. SRG based image segmentation

The conventional SRG is composed of three major steps, i.e. seeds selection, region growing and region merging. To select the initial seeds appropriately, the proposed method has one more step of pre-processing than the conventional SRG. The entire proposed segmentation method is now introduced in detail below.

4.1. The pre-processing of SRG

First, we use the edge detection method proposed in Section 2 to determine $CE_{i,j}$ and $NCE_{i,j}$ of each pixel. Then, use (7) to detect the fuzzy similarity $S_{i,j}$ between each current pixel $\mathbf{x}_{i,j}$ and the corresponding neighbors.

$$S_{i,j} = 1 - \frac{1}{9}\sum_{n=1}^{9} \min\left(\frac{\|\mathbf{x}_n - \mathbf{x}_{mean}\|}{w_s}, 1\right), \tag{7}$$

where $\mathbf{x}_n$, $n = 1, 2, \ldots, 9$, and $\mathbf{x}_{mean}$ are nine pixels in the sliding window whose center is $\mathbf{x}_{i,j}$ and the mean of their vector, respectively. w_s is also a pre-defined parameter which affects the slop of the fuzzy membership function. If a small w_s is selected, the current pixel will be treated as the same similarity (i.e. $S_{i,j} = 1$) regardless $\|\mathbf{x}_n - \mathbf{x}_{mean}\|$ is small or big. w_s is also set to 0.4 in the common case.

4.2. Seeds selection

The initial seed pixel should have high similarity to its neighbors [4] and not on the edge or detailed region [2,3]. Therefore, the criterion of the initial seeds selection in this study is that

$$\text{If } \min(NCE_{i,j}, S_{i,j}) \geq T_{i,j}, \text{ then } \mathbf{x}_{i,j} \text{ is a seed}, \tag{8}$$

where $T_{i,j}$ is a threshold determined by a fuzzy rule base introduced in Section 4.2.1.

4.2.1. Determining the threshold

The fuzzy rule base to determine the threshold $T_{i,j}$ has two input, $\bar{S}_{i,j}$ and $\overline{NCE}_{i,j}$. $\bar{S}_{i,j}$ and $\overline{NCE}_{i,j}$ are the mean fuzzy similarity and the mean fuzzy membership degree of "the current pixel is not a connected edge" in a 5×5 sliding window whose center is located at position (i, j), respectively. The big values of $\bar{S}_{i,j}$ and $\overline{NCE}_{i,j}$ mean that the current pixel and the current sliding window are on the smooth region. Otherwise the values of $\bar{S}_{i,j}$ and $\overline{NCE}_{i,j}$ are small mean that they are in the detail or edge region. In the smooth region, the threshold is set to small such that the seeds can appear in groups. In the detail or edge region, the threshold must be set as big to ensure the number of seeds in the detail is few. Therefore, the following fuzzy rule base is generated.

$$\text{Rule} - 1: \text{ If } \bar{S}_{i,j} \text{ is BIG and } \overline{NCE}_{i,j} \text{ is BIG, then } T_{i,j} \text{ is SMALL.} \tag{9a}$$

$$\text{Rule} - 2: \text{ If } \bar{S}_{i,j} \text{ is BIG and } \overline{NCE}_{i,j} \text{ is SMALL, then } T_{i,j} \text{ is BIG.} \tag{9b}$$

$$\text{Rule} - 3: \text{ If } \bar{S}_{i,j} \text{ is SMALL and } \overline{NCE}_{i,j} \text{ is BIG, then } T_{i,j} \text{ is BIG.} \tag{9c}$$

$$\text{Rule} - 4: \text{ If } \bar{S}_{i,j} \text{ is SMALL and } \overline{NCE}_{i,j} \text{ is SMALL, then } T_{i,j} \text{ is BIG.} \tag{9d}$$

where BIG and SMALL are linguistic variables. Since the inputs $\bar{S}_{i,j}$ and $\overline{NCE}_{i,j}$ are both fuzzy membership degrees already, i.e. $\bar{S}_{i,j}, \ \overline{NCE}_{i,j} \in [0, 1]$, the weights of each rules are directly determined as $w_1 = \bar{S}_{i,j} \cdot \overline{NCE}_{i,j}$, $w_2 = \bar{S}_{i,j} \cdot (1 - \overline{NCE}_{i,j})$, $w_3 = (1 - \bar{S}_{i,j}) \cdot \overline{NCE}_{i,j}$ and $w_4 = (1 - \bar{S}_{i,j}) \cdot (1 - \overline{NCE}_{i,j})$, respectively, by using the product inference engine [6]. The fuzzy sets of the output are singletons in which SMALL means $T_{i,j}$ is set to T_{small} and BIG means $T_{i,j}$ is set to T_{big}. In order to determine the output $T_{i,j}$, the center average defuzzification [6] is used as (10),

$$T_{i,j} = \frac{\sum_{r=1}^{4} w_r \cdot t_r}{\sum_{1}^{4} w_r}, \tag{10}$$

where t_r, $r = 1, 2, 3, 4$, are $[T_{small}, T_{big}, T_{big}, T_{big}]$, respectively, derived from the rules (9a)–(9d). In our series of experiments, in which the identical threshold is used in the entire image, the fine results of seeds selection are obtained when the threshold are set in $[0.75, 0.95]$. Therefore, T_{small} is set to 0.75 and T_{big} is set to 0.95 in this study.

4.2.2. The post-processing of seeds selection

Each connected component of seed pixel is taken as one seed. Hence, the generated seeds can be one pixel or one region with several connected seeds. We assign a label number to each seeded region and record each regions' mean pixel value $\mathbf{R}_m$, $m = 1, 2, \ldots, M$, where M is the number of seeded regions. Then, we record the neighbors of all regions in a sorted list H, which denotes the set of pixels that are unlabeled and are neighbors of at least one region, in an increasing order of d_H. d_H is a measurement, which is different from the conventional SRG, composed of d and $CE_{i,j}$ shown in (11)

$$d_H = d \cdot CE_{i,j}, \tag{11}$$

where d is the fuzzy distance between the pixel in H, which is denoted as $\mathbf{x}_{i,j}^H$, and its neighboring seeded region m,

$$d = \min_{m=1,2,\ldots,M} \left(\frac{\left\| \mathbf{x}_{i,j}^H - \mathbf{R}_m \right\|}{w_d}, \ 1 \right). \tag{12}$$

Significantly, the pixel in H with minimal d will be firstly assigned to one of neighboring regions in the conventional growing step. In the proposed method, if the pixel in H is on the edge, the corresponding d_H is generally larger than the pixels which are not on the edge because of the term $CE_{i,j}$ in (11). Therefore, it ensures that the pixel on the edge is processed later than other pixels in H in the region growing step. Noted that if $\mathbf{x}_{i,j}^H$ is a neighbor of not only one regions, only the minimal d_H, which is the fuzzy distance between $\mathbf{x}_{i,j}^H$ and the most similar neighboring region, is recorded.

4.3. Region growing

In this step, the seeded regions grow pixel by pixel. Let us check the first one pixel in H, i.e. the pixel in H with the minimal d_H, the neighbors of this pixel have three cases: First, if only one neighbor is labeled, the pixel is labeled as the same region. Second, if more than one neighbor are labeled and the labels are the same, the pixel is labeled as the same region. Third, if more than one neighbor are labeled and the labels are different, the pixel is labeled to the region that has the minimal d to the pixel. After the pixel is labeled to one region, we remove it from H and add its unlabeled neighbors into H. Thus update the regions' mean $\mathbf{R}_m$, $m = 1, 2, \ldots, M$. The region growing step works iteratively until H is empty, i.e. all pixels in the image are labeled.

4.4. Region merging

Finally, merging the similar image regions via checking the fuzzy distance between each region and the size of each region is necessary in order to avoid the over-segmentation. The fuzzy distance between the pair of regions p and q, $p, q \in \{1, 2, \ldots, M\}$, $p > q$, is shown in (13).

$$d_{p,q} = \min \left(\frac{\left\| \mathbf{R}_p - \mathbf{R}_q \right\|}{w}, 1 \right). \tag{13}$$

The pair of regions with the minimal fuzzy distance $d_{p,q}$ are merged together. Furthermore, the region with the size smaller than 1/100 of the pixels number in the entire image is merged into its most similar neighboring region. The region merging also works iteratively until the minimal $d_{p,q}$ is larger than 0.1 and the size of the smallest region is larger than 1/100 of the entire image.

5. Simulations

The illustration of the proposed image segmentation is shown in Fig. 3. Fig. 3(a) is the color image "boat". The connected edge map CE and the fuzzy similarity S of "boat" are shown in Fig. 3(b) and (c), respectively. The fuzzy membership degrees are normalized into [0,255] in order to represent CE and S as images. Which the large fuzzy membership degree leads to the bright image intensity. Fig. 3(d) shows the initial seeds which are denoted as red points. Fig. 3(e) is the region growing result which is not processed yet with region merging. Finally, the image segmentation result with region merging is shown in Fig. 3(f).

In order to test the image segmentation capability of the proposed method, the simulation results were compared with the

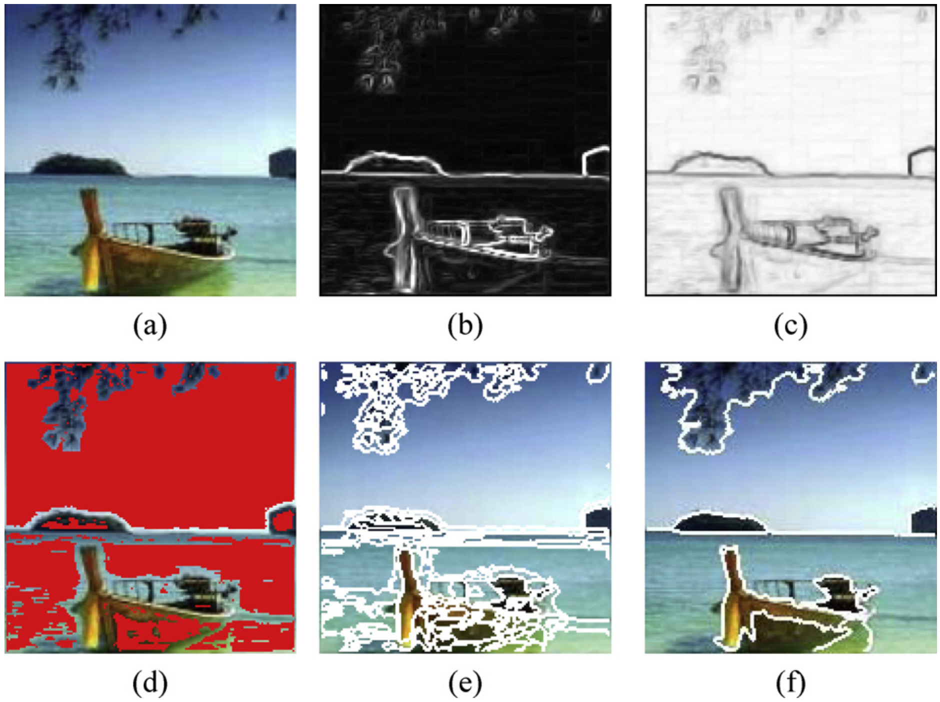

Fig. 3. The processes of the entire proposed image segmentation method: (a) the original image, (b) the connected edge *CE*, (c) the fuzzy similarity *S*, (d) the result of initial seeds selection, (e) the result of regions growing and (f) the result of regions merging.

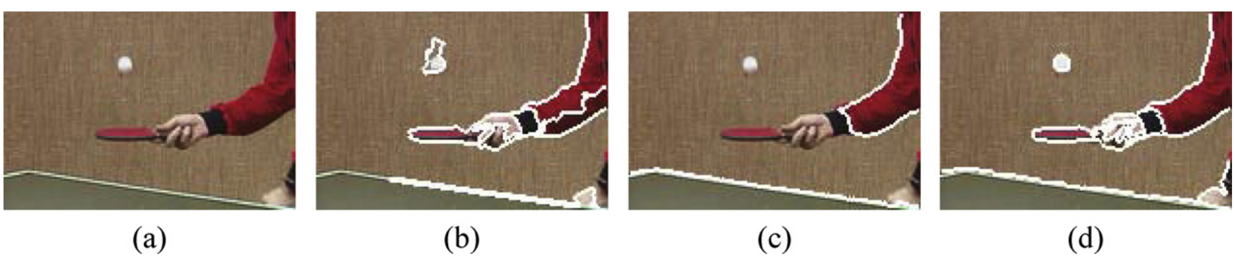

Fig. 4. The simulations of the image segmentation on the color image “tennis”: (a) the original “tennis” image, (b) using the method in [4], (c) using the method in [5] and (d) using the proposed method.

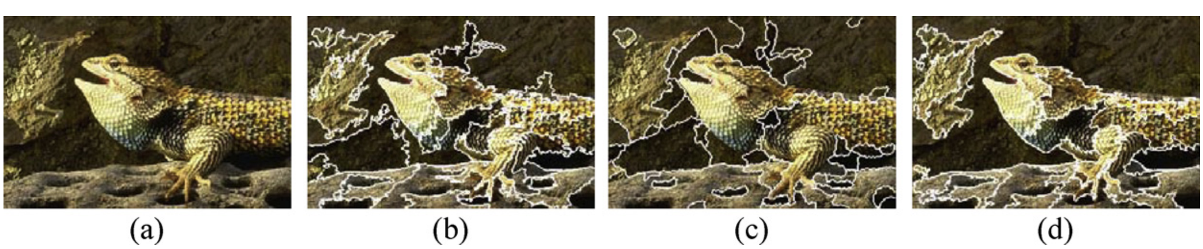

Fig. 5. The simulations of the image segmentation on the color image “lizard”: (a) the original “lizard” image, (b) using the method in [4], (c) using the method in [5] and (d) using the proposed method.

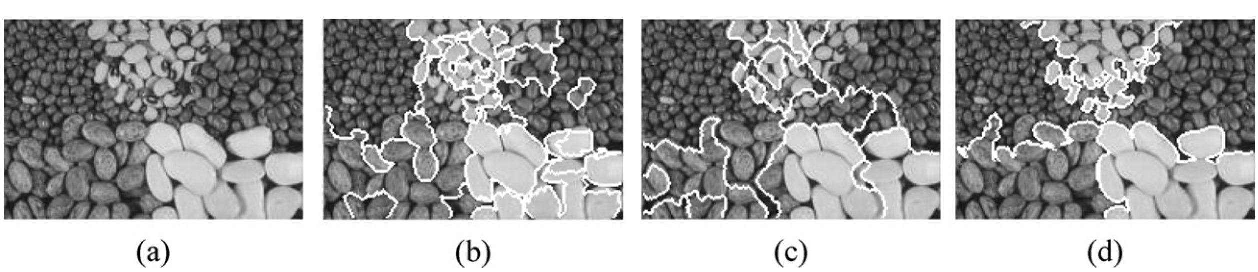

Fig. 6. The simulations of the image segmentation on the gray level image “beans”: (a) the original “beans” image, (b) using the method in [4], (c) using the method in [5] and (d) using the proposed method.

results by the methods in [4] and [5]. Figs. 4–6 show the simulations of "tennis", "lizard" and "beans" images, respectively. Both "tennis" and "lizard" images are color images, while "beans" image is the gray level image. Figs. 4–6(a) are the original images. Figs. 4–6(b)–(d) are the segmentation results of using the methods in [4], [5] and the proposed method, respectively. All parameters were the best values recommended in the corresponding papers. Since the method in [5] has the random process in color quantization, the results were different in each time of simulations. From the simulation results, we can see that the proposed method outperforms other seeded region growing based image segmentation methods.

6. Conclusions

This study proposes a novel SRG to realize the color and gray level images segmentation in complicated background. The fuzzy edge detection in our previous research is modified to detect the connected edge in this study. The initial seeds without the detail and complicated background are selected automatically by combining the fuzzy similarity. Each initial seed corresponds to an image region and the regions grow gradually by checking the fuzzy distance between the pixel and its neighboring seeded regions until the entire image is segmented. The conventional region growing is also modified to ensure that the pixel on the edge is processed later than other pixels. Finally, the region merging is applied to the similar or the extremely small image regions for avoiding the over-segmentation. The simulations show that the proposed method is better than other existing seeded region growing based image segmentation methods.

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