A Noble Image Segmentation Using Local Area Splitting and Merging Method based on Intensity Change

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Abstract

This paper proposes a new image segmentation algorithm that involves local area splitting and merging based on intensity change. Most image segmentation algorithms take advantage of features such as pixel intensity and edge to split or merge an image. Therefore, in addition to susceptibility to noise, the latter algorithms have a problem in that they achieve different results depending on the initially selected seed location. The proposed method adaptively changes pixel intensity during the process of region segmentation to the representative intensity of the adjacent sub-area of high homogeneity. Therefore, this method is not affected by the initial seed location, and it also eliminates pre-process, such as noise removal, because the pixel intensity is progressively stabilized to the average value of object. In addition, this method preserves the edges of segmented objects and reduces the phenomenon of excessive region merger by determining the direction of the next merger upon splitting a local area into small sub-areas. Our experimental results demonstrated that the proposed method accurately segments images higher credibility than the existing image segmentation algorithms.

Keywords: Image processing, Image Segmentation, Splitting, merging, Intensity Change

1. Introduction

Image segmentation techniques allow distinction between many areas of an object image based on the features of the image data. They have also been utilized in the pre-process stage for image analysis and object recognition in diverse fields where image is used as input data. Image segmentation techniques process data based on the similarity and discontinuity to the grouping of input image data, which segments an image into many regions, each having a unique homogeneous feature compared to the adjacent regions [1, 2]. The efficiency of image segmentation depends on standard conditions, such as the kind of feature information used for grouping, the credibility of feature extraction and merging of feature information. Existing image segmentation techniques can be categorized into 3 general groups by method: (1) a method based on the threshold of histogram, (2) based on the edge present in image, and (3) based on region [3, 4]. The threshold based method presumes that clear distinction is possible between objects if each has a unique homogeneous intensity. On this presumption, this method obtains the threshold of intensity to segment an image into many regions. This method shows low credibility in region classification when the object image has unclear edges between regions or has numerous complicated regions. The edge based method classifies regions by extracting the edges between the regions with different features. If the extracted edges are not connected to each other, post-processes such as edge tracking and gap filling are required to connect them together. The region based method presumes that pixels
in the same region are similar in such features as brightness, texture and color. Based on the latter presumption, this method segments an image by merging or splitting adjacent pixels of homogeneous feature [5, 6]. The credibility of this method in area splitting is affected by initially selected features. Besides, there are combined methods for to improve region classification through region expansion by modifying or removing the edges of regions that have a homogeneous feature, or by taking advantage of the geometric feature and watershed method [7, 8]. In the present research, region segmentation was performed based on region by merging and splitting adjacent pixels having homogeneous features. In order to carry out merger, an attempt was made to split the local area containing a selected pixel into sub-areas. Then, the representative intensity of each sub-area was calculated. Furthermore the sub-area with the highest representative intensity homogeneity compared to that of the selected pixel was considered for the direction of the next merging. In addition, the proposed method dings allowed updating the selected pixel intensity to achieve merger with the representative intensity of the selected sub-area, in order to increase homogeneity within the region. Thus, the proposed method involves merging both pixel units and block units in a combined manner. Therefore the proposed method shows the effect of removing the noise present in the image, as well achieving excellent performance in splitting very small regions.

2. Proposed Method

In general, every region generated by image segmentation consists of pixels that have homogeneous features. Every pixel is initially assigned to a different region, and homogeneity of the adjacent regions is then verified prior to merging. The new region generated by merging 2 regions is assigned with smaller index values of the 2 regions (The 2 regions are distinguished via index value). As shown in Figure 1, the proposed region segmentation method can be divided into 2 steps: the first step is the segmentation of an image into many regions, and for the second is re-merging very small regions.

![Figure 1. Block Diagram of the Proposed Region Segmentation](image)

Unlike conventional region-based methods, the proposed region segmentation method does not set pixel intensity as a default feature for region segmentation; instead, it begins with the first pixel of an image. A local area of a fixed size is generated around the pixel under consideration. The local area is then divided into sub-areas, and the representative intensity of each sub-area is calculated. Then, in order to set the
direction of a new search, measurement is made as to the homogeneity of the calculated representative intensity in comparison with the intensity of the pixel under consideration. In the mean time, the intensity of the pixel under consideration is changed to the representative intensity of the sub-area that had the highest homogeneity compared to that pixel. Such a process is repeated, and each of the resulting regions is subjected to the re-merging of extremely small areas.

2.1. Local Area Splitting

A real image shows a distribution of various intensities among pixels. Further, each region is distinguished by clustering similar intensities. It should be noted, however, that the boundaries between regions have various shapes. Therefore, if region segmentation ignores such shape diversity, it many result in the collapse of the regions that share a boundary whose signal is too weak to distinguish them. If the collapsed regions are important parts of the image, then it is impossible to achieve accurate image segmentation. For this reason, the proposed method set a local area of fixed size around the pixel under consideration for merger. Then, the pixels making up the local area are subjected to measurement to find out the similarity of intensity between them and, based on the result, to generate sub-areas each having unique homogeneous features. Figure 2(a) shows a local area with a size of $3 \times 3$; CP is the pixel under consideration for merger; and P0 ~ P7 are the adjacent pixels. Figure 2(b) shows the sub-areas, each consisting of pixels of a homogeneous feature, generated by local area splitting. Figure 2(c) shows the local area splitting steps of the proposed method.

![Figure 2. Local Area Splitting (a) before (b) after (c) Process Steps](image-url)

The proposed algorithm was designed to operate as follows. Decision on whether or not a local area should be split is made based on the distribution of intensity among the pixels in that local area. If the coefficient of variation is large in the area, then the area is recognized as having diverse boundary shapes and an attempt is thus made to split the area. However, if the value is small, then splitting does not occur because the pixels have similar intensities.
In Equations (1) and (2), \( S \) is the index number of sub-area; \( VI_S \) and \( CV_{IS} \) are the variation and coefficient of variation, respectively, for the \( S^{th} \) splitting; \( S_n \) is the number of pixels involved in the \( S^{th} \) splitting; and \( S_i \) is the \( i^{th} \) pixel involved in the \( S^{th} \) splitting. After decision has been made to split into sub-areas, actual local area splitting is carried out based on Equation (3), defined as follows:

\[
I_S = \begin{cases} 
I_{S_i} + 1 & \text{if } S_i - S > S \times WT \\
I_{S_i} & \text{otherwise}
\end{cases}
\]

The index number \( S \) of the \( i^{th} \) pixel that satisfies the condition of Equation (3) is increased. Here, \( I \) is the index mask of local area and stores the index number of the splitting into sub-areas. \( I_{S_i} \) is the \( i^{th} \) pixel whose index number in the mask is \( S \); \( \bar{S} \) is the average for the pixels whose index number is \( S \); and \( WT \) is weight, controlling the splitting into sub-areas. Figure 3 shows the proposed local area splitting algorithm.

1) Initialize \( I_{S_i} = 1 \), \( \forall i \) into local area
2) Iterate, if \( split\_index \leq 0 \) then stop
   else opt=false
   2.1) if \( split\_index = I_{S_i} \), then cal. \( CV_{IS} \)
   2.2) if \( CV_{IS} > 0.5 \) and \( split\_index = I_{S_i} \), then
       2.2.1) if \( S_i - S > S \times WT \)
           then, \( I_{S_i} = \text{split\_index} + 1 \), opt=false
   2.3) if opt = true then \( split\_index += 1 \)
       else \( split\_index -= 1 \)

**Figure 3. Local Area Splitting Algorithm**

As shown in Figure 3, the proposed region segmentation method can be divided into 2 steps: a step for segmenting an image into many regions, and a step for re-merging very small regions.

**2.2. Setting the Direction of Merger and Intensity Change**

The representative intensity of each of the sub-areas that had been generated from the index mask achieved via local area splitting was obtained by calculating the average intensity of the pixels belonging to each sub-area, using Equation (4):

\[
VI_S = \frac{\sum_{i=1}^{n} S_i^2 - (\sum_{i=1}^{n} S_i)^2 / n}{S_n - 1}
\]

\[
CV_{IS} = \frac{S_n \times VI_S \times 100}{\sum_{i=1}^{n} S_i}
\]
\[ R_s = \frac{1}{S_n} \sum_{i=1}^{S_n} S_i \]  \hspace{1cm} (4)

Then, the direction of merger was decided toward the sub-area that showed the minimum intensity difference when compared to the pixel under current consideration. The intensity difference was calculated using Equation (5):

\[
 DR_s = \begin{cases} 
 1 & \text{if} \min(|R_s - CP| < IL), \forall S \\
 0 & \text{otherwise} 
\end{cases} \hspace{1cm} (5)
\]

Here, \( DR_s \) is the sub-area containing the pixels with the highest similarity to the pixel under current consideration (\( CP \)). In order to eliminate excessive merging with other sub-areas containing pixels of high similarity to the pixel under current consideration, the threshold of intensity difference (\( IL \)) was set. Thus, the direction of the next merger was set toward the sub-area of the smallest intensity difference among the sub-areas whose intensity did not exceed the threshold. In the mean time, in order to increase homogeneity, intensity of the pixel under current consideration was updated with the representative intensity of the sub-area to be merged. Such an intensity change has the effect of removing the noise present in the image without a separate pre-process. Figure 4 shows the steps of deciding the direction of the next merger via the proposed method.

![Diagram](image)

**Figure 4. The Steps of Intensity Changing and Merger Direction Setting; (a) Sub-area Selection and Intensity Change; (b) Next Merger Direction Setting; (c) Region Index Setting**

Figure 4(a) shows that the sub-area whose representative intensity had the highest similarity to the intensity of the pixel under current consideration (\( CP \)) was selected out of many sub-areas. Figure 4(a) also shows that the intensity of pixel (\( CP \)) was updated with the representative intensity of the selected sub-area. Figure 4(b) shows that the direction of the next merger was decided by the selected sub-area. It also shows; and that the same process was repeated with the pixels located in that direction, to expand that sub-area. Figure 4(c) shows that the index number of the pixel under current consideration (\( CRN \)) was extended to the pixels of the next merger. Figure 5 shows the algorithm for merger direction setting and intensity change.
2.3. Region Merger

Among the regions generated by the region segmentation of an input image, there are regions whose sizes are relatively compared to other regions. An attempt was made to merge such small regions into adjacent regions to reduce the number of the finally generated regions. Figure 6 shows the proposed steps of region merger. In Figure 6(a), Regions 3, 5 and 6, which are relatively small compared to other regions, are searched from image after completing the region segmentation, and are then registered as candidates for region merger with other regions. The registered candidates are organized in the according to region size, and attempts are made to carry out merger, beginning with the smallest one.

![Figure 5. Setting of Merger Direction Algorithm](image)

![Figure 6. The Steps of Region Merger; (a) Merger Candidate Selection; (b) Check Contiguity Region; (c) Merger Result](images)
In Figure 6(b), the regions adjacent to Region 6 are examined to find out the pixels that have the same region index number as that of Region 6. These pixels are selected to set the direction of the next examination, while the other regions are registered for merger with Region 6. Then, the region with the highest similarity to Region 6 is selected for merger out of the adjacent regions. The result of the merger is shown in Figure 6(c).

\[
CD_j = \frac{1}{C^j_n} \sum_{i=1}^{C^j} C^j_i
\]

(6)

\[
CR_k = \frac{1}{R^k_n} \sum_{i=1}^{R^k} R^k_i
\]

(7)

\[
CRN_j = \begin{cases} 
  k & \text{if } \min\{|CR_k - CD_j| < IL\}, \forall k \\
  j & \text{otherwise}
\end{cases}
\]

(8)

In these equations, \(CD_j\) is the average intensity of the candidate region with which merger will be attempted; \(C^j_i\) is the number of pixels belonging to the candidate region; and \(C^j_i\) is the \(i^{th}\) pixel. \(CR_k\) is the average intensity of the region adjacent to the candidate region; \(R^k_n\) is the number of pixels belonging to the adjacent region; \(R^k_i\) is the \(i^{th}\) pixel; and \(CRN_j\) is the index number of region segmentation. The proposed algorithm for region merger is shown in Figure 7.

1) Searching small region into segmented Image, and sorting.
2) Checking contiguity regions of searched regions from step 1 and register index number.
3) if \(|CR_k - CD_j| < IL\), then cal. intensity difference between \(CR_k\) and \(CD_j\)
4) Searching minimum of step 3).
5) if \(k\) is minimum by step 4), then set \(CRN_j = k\) otherwise set \(CRN_j = j\)

Figure 7. Region Merger Algorithm

3. Experimental Result

In order to verify the suitability of the proposed region merger algorithm, a comparative analysis was carried out between the proposed algorithm and the image segmentation algorithm based on K-mean and Mean-Shift. The images used for the experiment had intensity, and the experiment was carried out with the original images and the original images with Gaussian noise 10%, respectively. Information about the images used for experiment is shown in Table 1. Figures 8 and 9 shows the original images and the original images with Gaussian noise 10% used for experiment.
Table 1. The Information of Images

<table>
<thead>
<tr>
<th></th>
<th>Bookshelf</th>
<th>Peppers</th>
<th>Camera man</th>
<th>House</th>
</tr>
</thead>
<tbody>
<tr>
<td>Image size</td>
<td>256X256</td>
<td>256X256</td>
<td>256X256</td>
<td>256X256</td>
</tr>
<tr>
<td>IL</td>
<td>5</td>
<td>5</td>
<td>5</td>
<td>5</td>
</tr>
<tr>
<td>WT</td>
<td>0.15</td>
<td>0.15</td>
<td>0.15</td>
<td>5</td>
</tr>
</tbody>
</table>

Figure 8. Original Images (a) "Bookshelf" (b) "Peppers" (c) "Camera Man" (d) "House"

Figure 9. Images (Gaussian noise 10%) (a) "Bookshelf" (b) "Peppers" (c) "Camera Man" (d) "House"

In order to compare performance of the 2 algorithms, Figures 10 and 11 present the average intensities of the regions generated by the region segmentation algorithm based on K-mean and mean-shift. First, Figure 10 shows that the proposed algorithm achieved better results than the one based on K-mean and mean-shift. According to the result achieved by the region segmentation based on mean-shift with “camera man” image, the accuracy of image segmentation was low for the regions of uneven intensity distribution, although image segmentation result was always good for the regions of even intensity distribution. On the contrary, the result showed that the proposed method was not affected at all by intensity distribution.
Figure 11 shows the result of the same experiment carried out using the image with Gaussian noise 10%. The region segmentation based on K-mean and mean-shift was not good because of noise. In contrast, the proposed method achieved better performance in region segmentation than the other methods. The reason is that the proposed method does not depend on the feature of initial intensity, as it allows pixel intensity to be progressively stabilized with regard to adjacent sub-area during the region segmentation process, so as to increase region homogeneity.
Figure 11. The Result of Region Segmentation in Noise Images

Figure 12 shows the result of extracting interest regions from “bookshelf” image and “camera man” image. From the regions generated by the proposed method, interest regions were extracted by generating masks for the interest regions. The result shows that the overall region segmentation performance of the proposed method is accurate. Figure 12(a) shows the edges of the regions of interest, among the regions generated by the proposed segmentation method. Figure 12(b) shows the mask images of the interest regions, and Figure 12(c) shows the interest regions extracted from the images after region segmentation, as well as their edges. Finally, Figure 12(d) shows the result of extracting regions of interest from the original images.
Figures 13 and 14 show the stabilization of initial pixel intensity via intensity change in addition to the edges of generated regions, when region segmentation was completed by the proposed region segmentation algorithm using original images and noise images. Figures 13(a) and 14(a) show original images and noise images. Figures 13(b) and 14(b) show the images resulting from the updating of initial pixel intensity with the intensity of the adjacent areas after the completion of region segmentation. Figures 13(c), 13(d), 14(c) and 14(d) show the result of superimposing the edges of extracted regions on the edges of the corresponding regions of the original images (noise images). The result shows that the proposed algorithm performed accurate segmentation to reproduce the regions of the original images.
Figure 13. The Result of the Proposed Method about Original Images
4. Conclusion

This paper proposed a new image segmentation algorithm that involves local area splitting and merging based on intensity change. Conventional region segmentation depends on the similarity and discontinuity of input image data to generate regions each consisting of data of a homogeneous feature. However, the credibility of the regions generated by segmentation varies depending on the feature of the initial information used for grouping. Therefore, in order not to be affected by the feature of initial information, the proposed method was designed to split a local area into sub-areas and then determine the direction of merger direction by examining this sub-area. In addition, this method adaptively updates a pixel’s intensity with the representative intensities of the region to which it belongs, in order that a new intensity is used for next merger. In this way the feature of initial information is stabilized, and the homogeneity within the region is increased. Thus, the proposed method involves the merging of both pixel units and block units in a combined manner in order to preserve the edge. Therefore, the proposed method shows the effect of removing noise present in the image, as well as excellent performance in splitting small regions. Our experimental results also showed that the proposed method reduced the phenomenon of excessive region merger, demonstrating that it is a simpler and more accurate segmentation method than existing image segmentation algorithms. As a future research, the authors
are planning to expand the algorithm to make it applicable not only to grey scale image but also to color image.

References


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