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Image Segmentation Using both Edge and Region Information

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Abstract

This paper proposes a method for segmenting an image into *only* the regions segmentable reliably, using both edge and region information. It is important that lower level processes give useful information to upper level processes, for example, whether segmented regions are reliable or not.

So we first modified the definition of region segmentation proposed by Horowitz and Pavlidis[4] and determined the condition of a certain region which can be reliably segmented. The condition with predicates utilizes both edge and region information. Our method segments only the areas satisfying the condition into the certain regions starting with the subspaces with size-scale s, leaving the rest of the image as uncertain regions.

Introduction

The final goal of image segmentation is to segment an image into regions which compose meaningful parts of an object from a human's viewpoint. It seems impossible to attain that goal in only a bottom-up way. A priori knowledge of the objects or the scene and a top-down approach utilizing it may be necessary for a successful segmentation. However, we also have to consider that a segmentation at lower-level processes should give *useful* information to upper-level processes. For example, when we want to extract a region with some given structural attributes from an image, we will think of segmenting the image into regions at a lower-level process and test at an upper-level process whether the segmented regions match the specified region or not. In this case, identifying unreliable regions which have too small and complex structure in the lower-level segmentation can improve the matching efficiency and correctness.

Therefore, we propose here an image segmentation method for segmenting an image into certain and uncertain regions, as the first process of a bottom-up approach. Uncertain regions are the areas which we can not tell confidently they compose a region with a uniform feature, and should be used in a later process to look into more information in detail.

Initial Consideration

There have been proposed many methods of region segmentation and many features were used by those methods. A method which can segment a big variety of images successfully does not exist yet. We think that more abstract features should be used for more or less general-purpose region segmentation. By using such abstract features we also should present a more schematic algorithm of region segmentation.

Two abstract features have been used by many region segmentation methods: one is 'uniformity' and the other is 'edge'. Many specific features were proposed and used as actualization of the two abstract features. Here we first present our algorithm as schematically as possible in terms of 'region uniformity' and 'edge', then specialize it specifying those two features in a particular set of image and goal.

Basic Idea and Definition

First we modify the definition of image segmentation proposed by Horowitz and Pavlidis[4]. They defined the image segmentation as segmenting an image R into regions $R_1, R_2, \ldots, R_N$ such that :

(1) $\bigcup_{i=1}^{N} R_i = R, \quad R_i \cap R_j = \phi \quad \text{for } i \neq j$

(2) R_i is connected, $i = 1, 2, \cdots, N$

(3) $P(R_i) = \text{true} \quad i = 1, 2, \cdots, N$
where P is a predicate

(4) $P(R_i \cup R_j) = \text{false} \quad \text{for } i \neq j$
such that R_i and R_j are adjacent

Because every pixel must be in some region under the condition (1), many meaningless regions might appear in a segmentation. We want to extract the regions which compose apparently some meaningful part of an object in the image, by leaving the rest of pixels as uncertain to be analyzed in a later stage. So we modified the condition (1) as follows :

$$(1)' \quad \bigcup_{i=1}^{N} R_i \subseteq R, \quad R_i \cap R_j = \phi \quad \text{for } i \neq j$$

It is not necessary to segment a *whole* image under this new condition (1)'. In other words, if a pixel does not satisfy the condition (3), it does not have to belong to some region. We call an area constructed by connecting such pixels "an uncertain region", and call regions satisfying all conditions (1)'– (4) "a certain region".

Predicate for Certain Region

In this paper we use edge and region information to determine the *predicate* P in the condition (3). The edge information reflects a change of some feature between regions, and the region information is a measure of uniformity in a region.

Each information should indicate that "Edge is the condition of the region boundary" and "Uniformity is the condition of the region inside". Therefore we separate the predicate $P(R_i)$ into the predicate for the interior $P_1(Int(R_i))$ and the predicate for the boundary $P_2(Bdry(R_i))$. Here the interior and the boundary of region R_i are denoted by $Int(R_i)$ and $Bdry(R_i)$, respectively.

$$P(R_i) = P_1(Int(R_i)) \wedge P_2(Bdry(R_i)) \tag{1}$$

Then the predicate P_1 can be represented by the predicate P_e denoting *"is an edge"* and P_u denoting *"is uniform"* as follows :

Condition of region interior

$$P_1(Int(R_i)) = \overline{P_e(Int(R_i))} \wedge P_u(Int(R_i)) \tag{2}$$

The predicate P_2 becomes the complement of P_1, which is written as :

Condition of region boundary

$$\begin{aligned} P_2(Bdry(R_i)) &= \overline{P_1(Bdry(R_i))} \\ &= P_e(Bdry(R_i)) \vee \overline{P_u(Bdry(R_i))} \end{aligned} \tag{3}$$

The above formulae can be interpreted as: the interior of a certain region has uniform features and no edges, while its boundary is an edge and not uniform. Our method extracts only certain regions which satisfy the predicate P defined by Eqs.(1)-(3) and classifies the pixels not belonging to any certain region as uncertain.

Now we have to decide which features be used to construct the predicates P_e and P_u. However, since region features can not be determined for a single pixel, we start with a division of the image into subspaces of size-scale s and calculate the region feature for each subspace. Thus certain regions we can detect should have larger structures than the size-scale s. On the other hand regions with smaller structures than s will be left as uncertain regions. So certain regions are the ones which introduce global structural information and compose a uniform region reliably, while uncertain regions are the parts where we can not tell confidently without further detailed analysis possibly at upper-level processes.

Algorithm

Figure 1 sketches roughly the algorithm of our method.

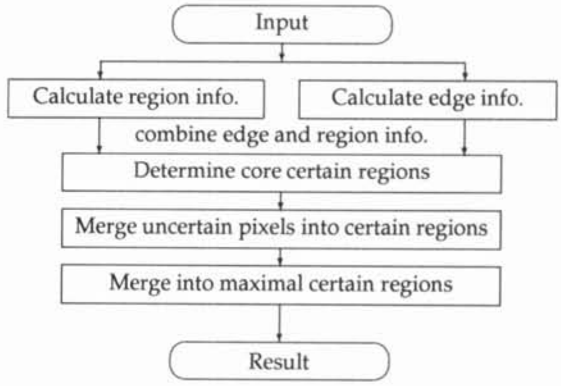


Figure 1: Algorithm of the proposed method

The first step is to calculate edge information and region information to construct the predicate P_e and P_u. For example, the edge information can be constructed by the result of the Canny's filter or the texture difference. The region information can be the mean intensity or the texture similarity. These features should be defined under one or more scale sizes s, and two or more thresholds are usually needed to define P_e and P_u. At the following steps we determine certain regions which satisfy Eq.(1), by using P_e and P_u.

Implementation and Result

We implemented the algorithm for gray scale image and used both the edge intensity and the mean intensity to express the predicate P_e and P_u, respectively.

We will explain in detail each step of the algorithm depicted in Figure 1 and show the results in Figure 2 (b)-(f) applied to the input image shown in Figure 2 (a) (256×256 pixels, 256 gray levels).

Calculate Information

At the first step, we calculate both edge and region information for each subspace of size $s \times s$ of a given image (Figure 2 (b), (c)). For the edge information we used the edge intensity calculated by using a filter of the shape of differential Gaussian function and for the region information the average intensity in each subspace. We emphasized this edge intensity by

$$E(x,y) = \begin{cases} 0, & \text{if } E_0(x,y) < \alpha\overline{E_0} \\ \log\left((e-1)\dfrac{E_0(x,y) - \overline{E_0}(x,y)}{E_{max}(x,y) - \overline{E_0}(x,y)} + 1\right) & \\ & \text{otherwise} \end{cases} \quad (4)$$

where $E_0(x,y)$ is the edge intensity value at (x,y), $\overline{E_0}(x,y)$ and $E_{max}(x,y)$ are the mean and the maximum edge intensity values in a small area around (x,y), respectively, $\overline{E_0}$ is the mean edge intensity value of the whole image, and e is the base of the natural logarithm. This equation normalizes edge intensity values from 0 through 1. α is a positive constant: we can control edge information by α, but usually $\alpha = 1$ suffices.

Determine Core Regions

At the second step, we merge subspaces (or regions) having consistent information into certain regions to obtain core regions where the predicate P_1 clearly holds (Figure 2 (d)). We determined P_1 as follows :

$$\begin{aligned} &P_1(Int(R_i \cup R_j)) \\ &\quad = \overline{P_e(Int(R_i \cup R_j))} \wedge P_u(Int(R_i \cup R_j)) \end{aligned} \quad (5)$$

$$\begin{aligned} &P_e(Int(R_i \cup R_j)) \\ &\quad = \begin{cases} \text{true} & \text{if } E(Bdry(R_i) \cap Bdry(R_j)) \geq \varepsilon_e \\ \text{false} & \text{otherwise} \end{cases} \end{aligned} \quad (6)$$

$$\begin{aligned} &P_u(Int(R_i \cup R_j)) \\ &\quad = \begin{cases} \text{true} & \text{if } \left|\overline{I(Int(R_i))} - \overline{I(Int(R_j))}\right| < \delta_i \\ & \quad \wedge E(Int(R_i)) = 0 \wedge E(Int(R_j)) = 0 \\ \text{false} & \text{otherwise} \end{cases} \end{aligned} \quad (7)$$

where $E(Bdry(R_i) \cap Bdry(R_j))$ is the average edge intensity of the boundary between region R_i and R_j, $\overline{I(Int(R_i))}$ is the mean intensity of region R_i interior, $E(Int(R_i))$ is the maximum edge intensity in the interior region R_i, ε_e is the edge intensity threshold for discriminating regions, and δ_i is the threshold for region homogeneity. P_1 behaves here as the condition for merging subspaces (or regions) R_i and R_j. $E(Int(R_i)) = 0$ guarantees that the intensity is uniform in each subspace composing region R_i, though the intensity may change gradually from subspace to subspace.

Settle the Boundaries

At the third step, we merge pixels in uncertain areas into an adjacent certain region to enlarge the core certain regions and settle their accurate boundaries using mainly the predicate P_2 for region boundary (Figure 2 (e)). We have to construct the predicate P_u for merging a certain region and a pixel. As only one pixel cannot have the mean intensity, we assumed that the mean intensity of a pixel is the mean intensity of an area of size $s \times s$ around the pixel. Since it is not sure whether a pixel locates inside or on the boundary of a certain region, we have to discriminate these two cases by mean of the edge intensity $E(X_j)$ of the pixel X_j. If the pixel seems to lie on the boundary, test the predicate P_2, otherwise test the predicate P_1. That is,

(i) if $E(X_j) > 0$, test the predicate P_2

$$\begin{aligned} &P_2(Bdry(R_i \cup X_j)) \\ &\quad = P_e(Bdry(R_i \cup X_j)) \vee \overline{P_u(Bdry(R_i \cup X_j))} \end{aligned} \quad (8)$$

(ii) otherwise (apply the predicate P_1)

$$\begin{aligned} &P_1(Int(R_i \cup X_j)) \\ &\quad = \overline{P_e(Int(R_i \cup X_j))} \wedge P_u(Int(R_i \cup X_j)) \end{aligned} \quad (9)$$

$$\begin{aligned} &P_e(Bdry(R_i \cup X_j)) = P_e(Int(R_i \cup X_j)) \\ &\quad = \begin{cases} \text{true} & \text{if } E(Bdry(R_i) \cup Bdry(X_j)) \geq \varepsilon_e \\ \text{false} & \text{otherwise} \end{cases} \end{aligned} \quad (10)$$

$$\begin{aligned} &P_u(Int(R_i \cup X_j)) = P_u(Bdry(R_i \cup X_j)) \\ &\quad = \begin{cases} \text{true} & \text{if } \left|\overline{I(Int(R_i))} - \overline{I(S(X_j))}\right| < \delta_i \\ \text{false} & \text{otherwise} \end{cases} \end{aligned} \quad (11)$$

where $S(X_j)$ is an area of size $s \times s$ centered X_j. If the X_j is admitted to belong to the region R_i, that is, the predicate P_1 is true, then X_j is merged into the region R_i.

Merge into Maximal Regions

At the final step, we merge certain regions into largest certain regions to meet condition (4), eliminating also small regions (Figure 2 (f)). We use the predicate P_1 for the merging condition as in Eqs.(6) and (7), but drop out the constraints $E(Int(R_i)) = 0$ and $E(Int(R_j)) = 0$ because they should already hold.

Scale-Space Approach

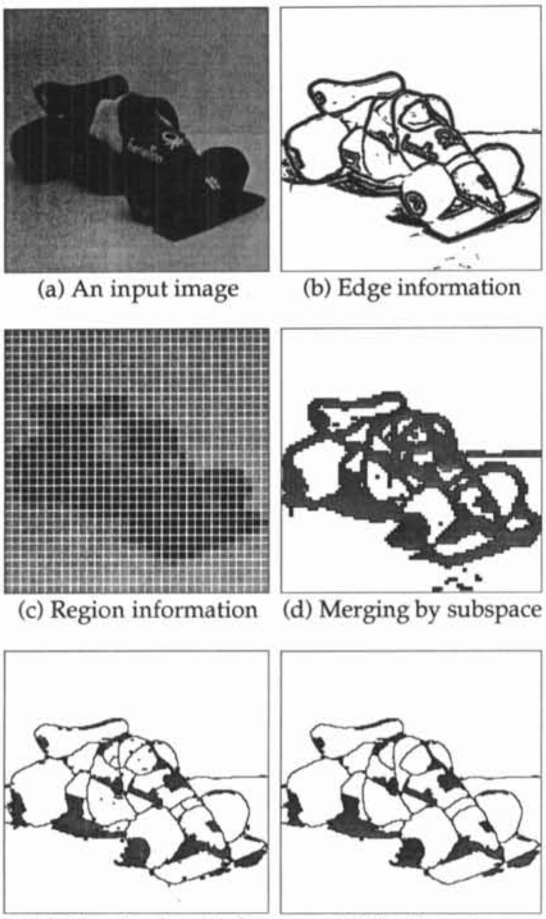
We can use a scale-space approach by controlling size s. That is, we segment the image using a large size-scale s at first, then apply our method to uncertain regions repeatedly, with decreasing s. In Figure 3, we illustrated the result of the scale-space approach applied to the input image shown in Figure 2(a). When applied with $s = 24$, the regions with their structure size bigger than 24 are extracted as certain, while the regions with smaller structures are left uncertain (Figure 3 (a)). We can detect more certain regions with smaller $s = 12$, applied to those uncertain regions of the previous result (Figure 3 (b)). The process is repeated with $s = 6$ and 4 and yields Figure 3 (c), (d).

This approach is effective for images having different scale objects.

Conclusion

We reformalized the definition proposed by Horowitz and Pavlidis and considered how a certain region can be defined. As the first stage of bottom-up segmentation process, we proposed a method for segmenting an image into certain regions and uncertain regions under the size-scale s.

This method satisfies the new definition and uses two complementary sources of information, namely,

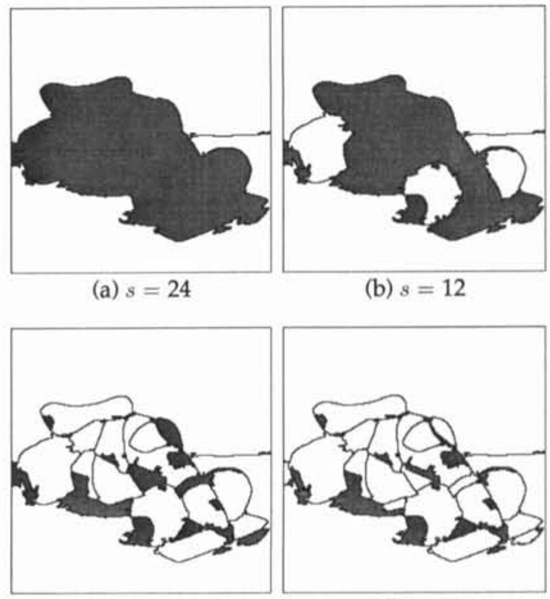


(a) An input image (b) Edge information

(c) Region information (d) Merging by subspace

(e) Merging by pixel (f) Final result

Figure 2: Result of each step



(a) $s = 24$ (b) $s = 12$

(c) $s = 6$ (d) $s = 4$

Figure 3: Result of a scale-space approach

edge and region features, to construct the predicate P which defines the certain regions.

At the end of the process, uncertain regions shrink to those areas which have complex structures of intensity. The detectable structures depend on the size-scale s of the initial division of the image into subspaces. This suggests a scale-space approach, which proves effective.

Acknowledgement

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