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Multi-class region growing algorithm

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Abstract

An automated region growing algorithm has been adapted for multi-class segmentation. The algorithm does not need initial parameters. It automatically finds a start region which is required by each of the region growing processes performed during multi-class segmentation. A new method for finding start region is proposed. The multi-class region growing algorithm was tested on CT and MRI scans.

1. Introduction

Image segmentation is an important research area in image processing, especially in medical applications. With development in CT and MR imaging, acquisition of high quality images is possible. However, in order for these images to be an effective support in diagnosis or quantitative analysis, they must be processed to extract relevant parts of the anatomy [1-2]. Segmentation is a very important step, which determines the accuracy of subsequent processes.

2. Definitions

A structuring element can be thought of as a filter mask $S(x, y)$ in which coefficients take binary values [3]. These values are chosen so that the mask specifies the origin neighborhood's desired shape (Figure 1).

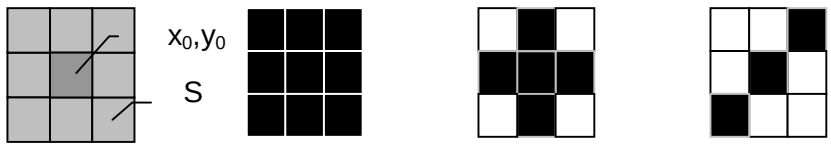

Fig. 1. Structuring element with labeled origin and most commonly used neighborhood shapes

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Dilatation is used to add ON pixels at the region boundaries [3-4]. When a structuring element is over a region, an OFF pixel at the origin is set to ON if any of the structuring element overlaps ON pixels of the image (Figure 2b). More formally, this may be expressed as:

$$I^D(x_0,y_0)=\begin{cases} ON & \text{if } I(x_0,y_0)=ON \text{ or } I(x,y)\wedge S(x-x_0,y-y_0)=\text{ON}, \\ & \text{for any } (x,y)\in N_S(x_0,y_0) \\ OFF & \text{otherwise} \end{cases}$$

where I^D is a dilated image, I is an original image, S is a chosen structuring element and N_S is a neighborhood of a pixel at the origin (x_0,y_0).

Erosion is used to remove ON pixels at the region boundaries [3-4]. When a structuring element is over a region, an ON pixel at the origin is set to OFF if any of the structuring element overlaps OFF pixels of the image (Figure 2c). More formally, this may be expressed as

$$I^E(x_0,y_0)=\begin{cases} ON & \text{if } I(x_0,y_0)=ON \text{ and } I(x,y)\wedge S(x-x_0,y-y_0)=ON, \\ & \text{for all } (x,y)\in N_S(x_0,y_0) \\ OFF & \text{otherwise} \end{cases}$$

where I^E is an eroded image, I is an original image, S is a chosen structuring element and N_S is a neighborhood of a pixel at the origin (x_0,y_0).

Boundary is determined by performing a binary erosion of a region and comparing the result to the original, using the logical XOR operation (Fig. 2d).



(a) (b) (c) (d)

Fig. 2. Original region (a), dilated region (b), eroded region (c), boundary (d)

K-contraction of a region *R* is obtained by removing all the pixels which belong to *k*-extreme non-void histogram bins [1] (Figure 3).

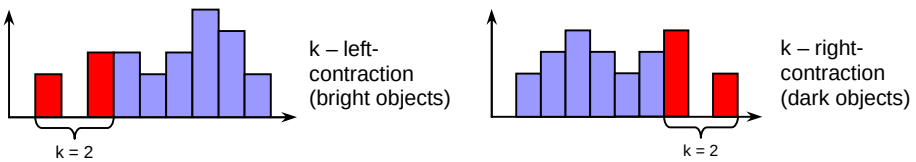

Fig. 3. Examples of 2-left-contraction (a), 2-right-contraction (b)

Homogenous region is a region whose standard deviation s is less or equal to a given homogeneity threshold s_{max} [1].

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3. Region growing algorithm

The region growing algorithm, which has been implemented, is a slightly modified version of the algorithm proposed by Revol and Jourlin [5]. It has the ability to segment non-connected regions. The pixels, which belonged to a homogenous region at a certain step, can be removed later. This property limits the chaining effect of classical region growing and allows to segment complex region, not requiring a seed point in all of its parts. The modification, mentioned above, allows the algorithm to work only on a selected part of the image. This is achieved by performing a logical AND operation on binary images describing a dilated region and the selected part of the image.

This algorithm is able to segment images with bimodal histograms. When the object is brighter than the background the left-contraction is used, otherwise the right-contraction is used.

At each step a homogenous region R_n is dilated yielding region R_{n+1}. If R_{n+1} is homogenous, the algorithms proceeds to the next iteration. Otherwise it reduces R_{n+1} histogram's dynamic range by performing 1-left-contractions or 1-right-contractions until R_{n+1} is homogenous and the algorithm can proceed to the next step. The following presents a pseudo code description of the region growing process used.

```
n ← 1;
R0 ← 0;//one before last = empty
R1 ← Ms;//last = seed points
while (Rn ≠ Rn-1)// are regions different?
      Rn+1 ← Dilatation(Rn);
      Rn+1 ← Rn+1 and Mb; //limiting the region
      if (σRn+1 ≥ σmax)//is Rn+1 not homogenous
            do//contracting the histogram
      if (Object=bright)
                        Rn+1 ← LeftContraction(1,Rn+1);
      else Rn+1 ← RightContraction(1,Rn+1);
    while (σRn+1 > σmax);// is Rn+1 homogenous
  end;
    n ← n+1;//next iteration
end;
RG ← Rn;//result
```

4. Automating the region growing process

The concept of automated region growing was introduced by Revol, Peyrin, Carrillon and Odet in [1]. The automated region growing process consists of three steps (Figure 4). In the first step an image is segmented for each s_{max} value within a given range (s_0 - s_3). Each time a start region is initialized with the

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same set of seed points. After each region growing process, the s_{max} value is increased by Ds until it reaches s_3. The result of this step is a sequence of segmented regions and s values associated with them (*the region growing sequence*). In the second step the quality of the segmentation is assessed. The third step consists in the determination of the optimal value of the standard deviation and, therefore, the optimal segmentation. In this approach the maximum value of the assessment function corresponds to the best segmentation in the sequence.

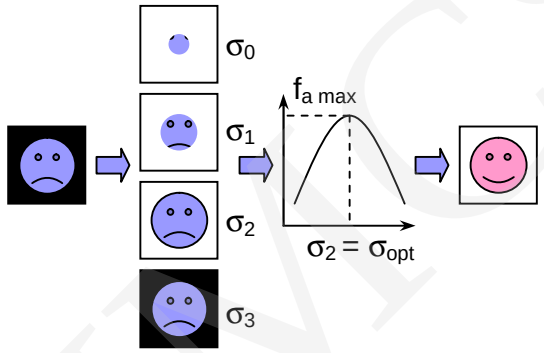

Fig. 4. Principle of an automated region growing

5. Segmentation quality assessment

The aim of $f_a(s)$ is to assess the quality of the segmentation of each region in the region growing sequence in order to detect the optimal homogeneity threshold s_{opt} for the region growing process. Two basic approaches are possible: by boundary or by region. In the first case the best segmentation corresponds to the regions whose boundaries present the strongest edge, in the second case, the best segmentation corresponds to the most homogenous region in the original image.

In the boundary approach many different assessment functions are possible, including functions based on a logarithmic image processing model, standard deviation or transition levels. The boundary B_R of a region is defined as the difference between the region and the same region after binary erosion.

In region approach types of assessment functions include those based on entropy, distance from the gray level function (image), and inter-cluster variance. Only LIP Contrast and entropy methods will be described since they turned out to be best suited for multi-class segmentation.

5.1. LIP contrast

Jourin and Pinoli [6] introduced a new mathematical model called the logarithmic image processing (LIP) model, which is well suited for logarithmic

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image processing (X-Ray images for example). Assessment function is defined as a sum of LIP contrasts c_f of all possible transition couples (figure 5) normalized by the total number N_{tc} of all transition couples.

$$c_f(x,y) = \frac{|f(x) - f(y)|}{1 - \frac{\min(f(x), f(y))}{M}},$$

$$f_a(s_{\max}) = \frac{\sum_{x \in B_{R(s_{\max})}} \sum_{y \in N_x} (c_f(x,y))}{N_{tc}}, \quad y \notin R(s_{\max})$$

where $f(x)$ and $f(y)$ are pixels' values, M is the number of available gray levels (for example $M = 256$ if pixels are coded using 8 bits) and N_x is the boundary pixel's x neighborhood.

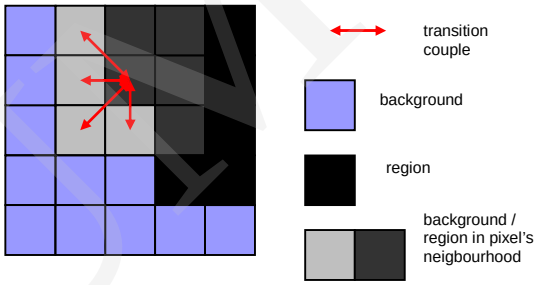

Fig. 5. Transition couples

5.2. Maximum entropy

Entropy is commonly used for optimal image thresholding [3]. This method consists in maximizing the sum of the entropies of the two classes into which the automated region growing divides the image. If $\overline{R}$ is the complement (background) of R (object) and p_{iR}, $p_{i\overline{R}}$ are the probabilities of individual gray levels, then the sum of the entropies is defined as follows:

$$S(s_{\max}) = -\sum_{i=0}^{ng_R} p_{iR} \ln p_{iR} - \sum_{i=0}^{ng_{\overline{R}}} p_{i\overline{R}} \ln p_{i\overline{R}} .$$

6. Multi-class region growing

The main disadvantage of automated region growing introduced by Revol, Peyrin, Carrillon and Odet in [1] is that it segments only two classes – object and background. This limits its application to the images with a bimodal histogram. Typically, in medical images, there are more than two structures and, therefore, the segmentation algorithm should be able to segment more than two classes.

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Multi-class region growing is, in fact, a sequence of automated region growing processes. First, all pixels in the image are not assigned to any class. A start region is automatically determined, and an automated region growing process is started. As a result of this step the brightest class in the picture is obtained. Second, the pixels that belong to the first class are marked as assigned so that they cannot be assigned to any other class. A new start region is obtained, and another automated region growing process starts (Figure 6). Multi-class segmentation stops when no further class can be segmented.

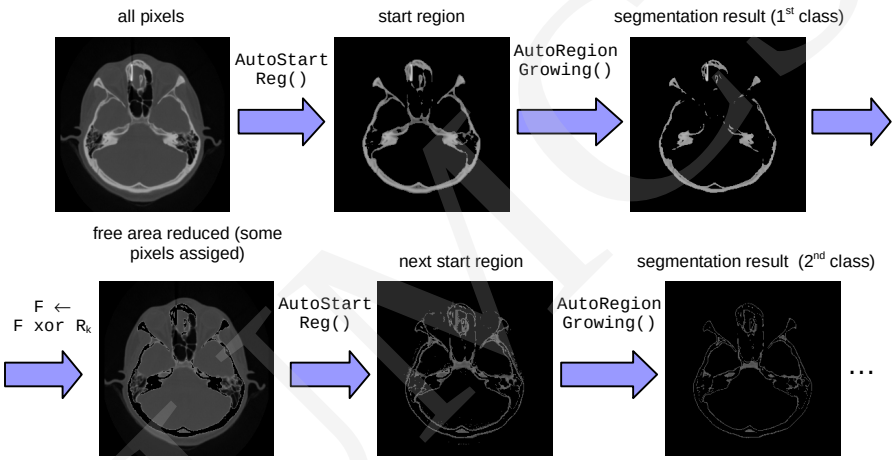

Fig. 6. Concept of multi-class region growing

```
n0 ← 0;
F ← Mb;//all pixels unassigned
n1 ← OnPointCount(F);//number of unassigned pixels
k ← 1;
while (nk≠nk-1)//has a new class been segmented?
Mt ← AutoStartReg(MinArea,F);//new start region
if (σconst=false) σr ← σ(Mt);//calculate s of new
 //start region
      Rk ← AutoRegionGrowing(0,5·σr,1,5·σr,Mt,F);
F ← F xor Rk;//mark pixels as assigned
k ← k+1;
nk-1 ← nk; //save the number of previously
                                  //unassigned pixels
nk ← OnPointCount(F);//new number of unassigned
                                  //pixels
end;
MCRG ← R1,R2,…, Rk-1;//segmentation result
```

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7. Obtaining the start region

Since each step of multi-class region growing requires a new start region, a way of obtaining it automatically is necessary. A simple method is used in multi-class region growing. The method used selects the brightest region (consisting of unassigned pixels) whose area is just above the minimum set arbitrarily (Figure 7). 1/10 of total number of pixels in the picture usually gives the best results.

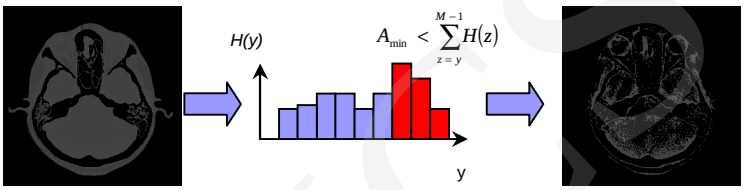

Fig. 7. Obtaining start region

8. Results

Below the results obtained using the multi-class region growing algorithm are presented (Figures 8 and 9). The algorithm has been tested on CT and MRI (T1) scans. As mentioned earlier, using LIP contrast and maximum entropy based assessment functions gave the best results. The results obtained with other assessment functions are presented for comparison.

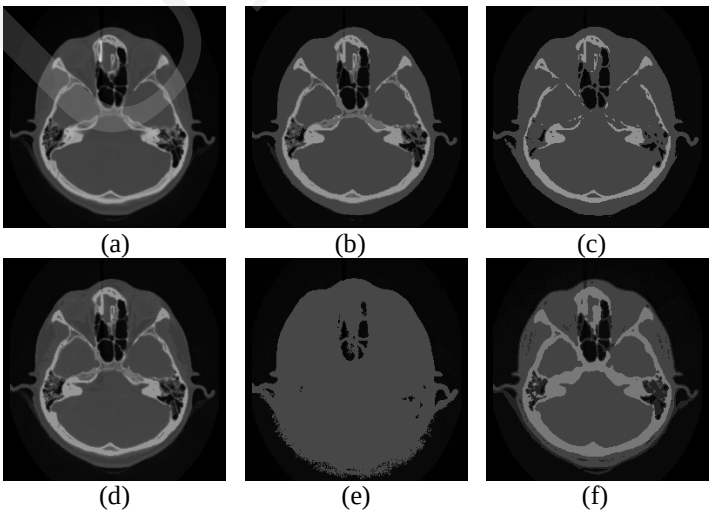

Fig. 8. Multi-class segmentation of CT scan, original image 256x256, 12bpp (a), LIP contrast – 6 classes (b), transition levels – 4 classes (c), standard deviation – 26 classes (d), distance from gray level function – 5 classes (e), maximum entropy – 6 classes(f)

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9. Conclusion

A multi-class region growing algorithm was presented. The optimal segmentation for each class is determined from an assessment function. Segmentation of 2D (256x256) image takes approximately 10-15 seconds on a computer with [a] 700Mhz Athlon CPU. The results obtained with a multi-class region growing algorithm were compared with segmentation performed by an expert. The maximum entropy method gave the closest results to the expert segmentation.

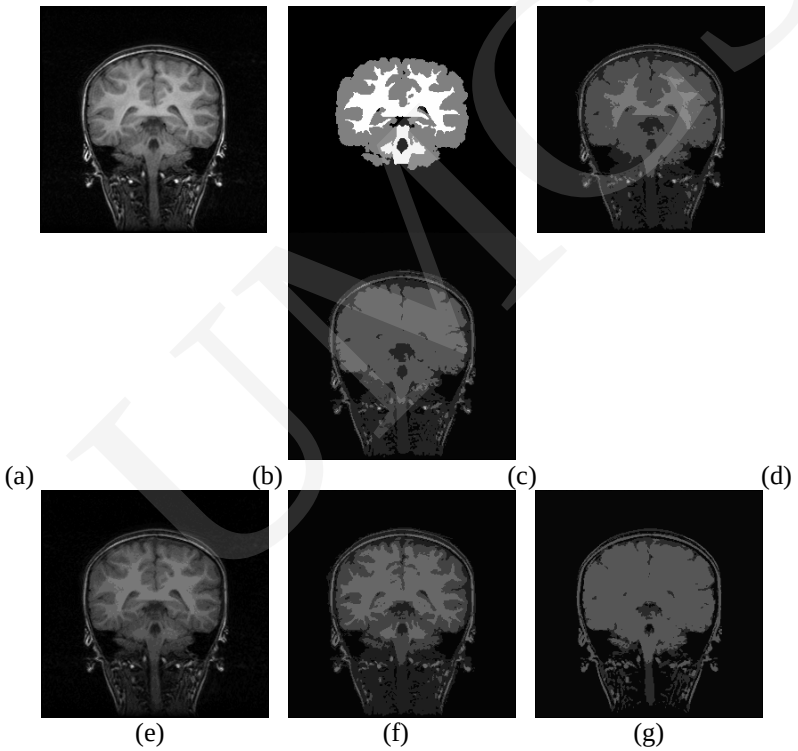

Fig. 9. Multi-class segmentation of MRI (T1) scan, original image 256x256, 8bpp(a), semi automatic segmentation performed by an expert (b), LIP contrast – 9 classes(c), transition levels – 8 classes(d), standard deviation – 21 classes (e), maximum entropy – 6 classes (f), distance from gray level function – 4 classes (g). (MR brain data set 1320_2_max and its manual segmentation was provided by the Center for Morphometric Analysis at Massachusetts General Hospital and is available at http://neuro-www.mgh.harvard.edu/cma/ibsr.)

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