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Yet Another Method for Image Segmentation based on Histograms and Heuristics *

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Abstract

We introduce a method for image segmentation that requires little computations, yet providing comparable results to other methods. While the proposed method resembles to the known ones based on histograms, it is still different in the use of the gray level distribution. When to the basic procedure we add several heuristic rules, the method produces results that, in some cases, may outperform the results produced by the known methods. The paper reports preliminary results. More details on the method, improvements, and results will be presented in a future paper.

Keywords: image processing, segmentation, mixed statistical-heuristic method, segmentation similarity index.

1 Introduction

Image segmentation is a recurrent subject in image processing journals and conferences. Although there is a huge number of segmentation methods proposed in the literature (see for example the reviews by Pal and Pal [1], by Cheng et al. [2], by Heimann and Meinzer [3], and by Mueller et al. [4]), none compares to the ability of human viewers to identify segments in images. This situation justifies the present proposal of segmentation procedure. In this section, we give

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the outline of the suggested segmentation method and its rationale. At our best knowledge, the procedure principle is new, although it has strong similarities with other well-known segmentation methods, see Zhang and Hu [5], Tobias and Seara [6], Khotanzad and Bouarfa, [7], and Kurugollu et al. [8].

Throughout this paper, we name segment a possibly disconnected subset of pixels of the image determined by a segmentation procedure. We name object any connected subset of a segment. With these terms, a segmented image is partitioned in a set of segments and every segment is partitioned in a set of objects. The purpose of the segmentation procedures is to determine such partitions that correspond to the elements of the image that are meaningful for a human observer. From this definition, we see that the segmentation problem is ill posed, because most segmentation procedures propose to perform segmentation based on geometrical and statistical properties of the image, while the result must be connected to information in the mind of the human observer, not in the image. Therefore, it is the opinion of the first author that any segmentation procedure must operate in two stages, the first one based on the geometrical and statistical properties of the image including some basic properties of connectedness, as in some graph-based approaches, while the second stage based on heuristic rules representing at least some elementary knowledge of the human viewer.

The paper deals with a novel way of using the global statistics of gray images for image segmentation. The statistics $p(G)$, where G is the gray level, is empirically represented by the histogram, $n(G)$. In the distribution function, instead of finding the 'valleys' or approximating it with a set of Gauss functions, as in other methods, we identify the intervals of almost constant probability, that is the intervals X_k satisfying one of the sets of conditions $\forall x_1, x_2 \in X_k \mid p(x_1) - p(x_2) \mid < \delta$ and $length(X_k) \geq \lambda \cdot G_{max}$, $0 \leq \lambda \leq 1$, with δ and λ predetermined parameters of the procedure, or $\forall X_k, STDV(X_k) < \delta$ and the second condition identical to the above. Once the intervals X_k are determined, the partition of the gray interval $[0, G_{max}]$ is completed with the remaining intervals. The segmentation of the image is performed according to the intervals X_k so determined. By varying the parameters δ and

λ, several segmentation results can be obtained. The method is further improved by automatically choosing the parameters such that the number of partition intervals is lower than a fixed number, for example $N = 5$. The obtained segments are labelled and further processed as explained in the final part of the paper.

The rationale of the method is as follows. A relatively constant value of the probability of occurrence of the gray levels in a quite large interval of gray levels may mean (that is, there is a great probability) that large patches of the image are uniform in gray level. Therefore, each of those regions should represent a significant object in the image and several such objects may occur in the image. Further, the intervals on the gray scale that are placed between the above determined intervals of almost-constant gray levels have large variations (larger than δ). These intervals correspond either to collections of small objects or to boundaries between larger objects. If they correspond to smaller objects, it is preferable to be retained as segments; when they represent boundaries that are segmented as different than the larger objects, they still can be merged with the larger objects in a subsequent phase using a dedicated procedure of merging. Thus, because at this stage we do not know if such lesser regions are objects or transition regions, they are preferably preserved as segments.

Notice that finding the intervals X_k is not trivial. These intervals are not necessarily unique. Explanations of the procedure used to determine a set of intervals X_k will be given in the next section. However, the proposed algorithm remains much simpler than other ones like those due to Kostas [9], Barret [10], or Udupa et al. [16].

2 Segmentation Algorithm

2.1 Basic algorithm – Preprocessing

The above principles need to be complemented with a set of techniques for preprocessing of the image as well as of the histogram. Image preprocessing is standard and comprises noise removal and weak smoothing of the gray level. For a 3×3 window, averaging filter is generally enough. Even so, the histogram of the gray levels in the image is typically very irregular. The irregularity of the histogram hampers the application of the procedure, because either a large number of (false) intervals or no interval at all may be produced. To eliminate this drawback, the histogram is smoothed by twice applying to it a mixture of median and low pass filtering with windows with 5 to 11 samples (see Annex). We then apply the segmentation procedure on the smoothed histogram. This preliminary phase is illustrated in Fig. 1.

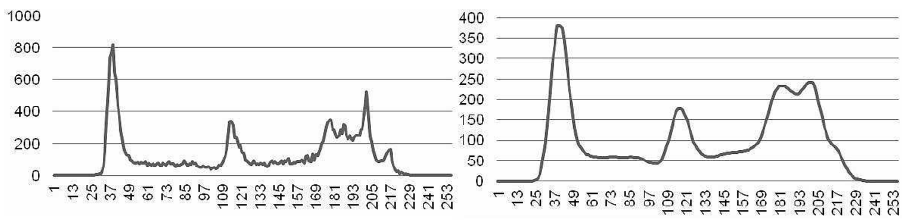

Figure 1. Example of preprocessing of the histogram

2.2 Basic algorithm: Segmentation

This sub-section follows [19]. The almost constant intervals were determined using an overlapping window of 24 samples considering the following rules:

1. $if\,\frac{V_{max}-V_{min}}{N_w} < 1.5$ then the interval is considered constant, where V_{max} and V_{min} are the maximum and minimum values of the window and N_w is the number of elements of the window. If two successive windows have this property we define the interval as being composed by both windows.

2. else the interval is considered not to be constant.

If we obtained several constant intervals, for the case with two thresholds we select the largest one, and its limits are considered thresholds. The segmentation is performed according to the example of pseudocode, were Th1 and Th2 are the limits of the largest quasi-constant

interval and $g(i,j)$ is the pixel value of the image:
if $g(i,j) < Th1$ **then** $g(i,j) \in$ **segment1**
if $g(i,j) \geq Th1$ && $g(i,j) \leq Th2$ **then** $g(i,j) \in$ **segment2**
if $g(i,j) > Th2$ **then** $g(i,j) \in$ **segment3**

If we use n thresholds, then there are $n+1$ segments.

2.3 Post-processing – Removing the bright reflection spots

One of the almost omnipresent defects in the segmentation of images of scenes illuminated artificially – and for many natural scenes too – is the appearance of bright spots due to reflections. Surprisingly, while this deficiency is mentioned in many papers, we have not found in the literature any reference to a method to get rid of them. However, heuristically speaking, it is obvious that such spots are the brightest; and consequently we can easily remove them by applying a rule in the post-segmentation stage a rule as 'Remove the brightest segment, whenever it has the characteristics of a spot of reflection, that is whenever its surface is much smaller (less than a given percentage) than the average surface of the objects in the image'. Notice that, to apply this rule in its full content, we need to compute beforehand the average dimension of the objects in the image.

3 Results

3.1 Segmentation results

We briefly illustrate the results obtained by our method and its variants and compare our segmentation results with several ones reported in the literature. We start with a simple case, of microscopic view of blood cells. The result is shown in Fig. 2 (original from [17]). The reader can visually compare our result with that in [6].

A typical test image used in the literature is the image of several

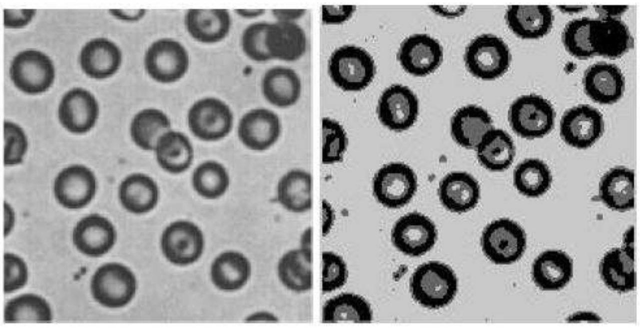

Figure 2. Simple segmentation case : blood red cells and nuclei. Left – original picture. Right: segmented, 2 thresholds. Compare to [6]

green sweet peppers [13]. The original image and two results obtained with our basic method, with the number of intervals X_k limited to 2, respectively 4, and correspondingly with 3, respectively 5 thresholds are shown in Fig. 3. These results compare well with those in the literature, see for example [14] and [18].

Figure 3. A typical test image: green sweet peppers. Left: original. Middle: segmentation with 2 thresholds. Right: 4 thresholds. Compare with [14]. Original picture from The USC-SIPI Image Database [13]

A difficult to segment case is a set of pictures recently published [12] and reproduced here with the kind permission of the author, Prof. Berkovitch. The 'giraffe' picture is however well segmented by the proposed method, see Fig. 4. For the original and filtered histograms for the giraffes in Fig. 4, see Fig. 5.

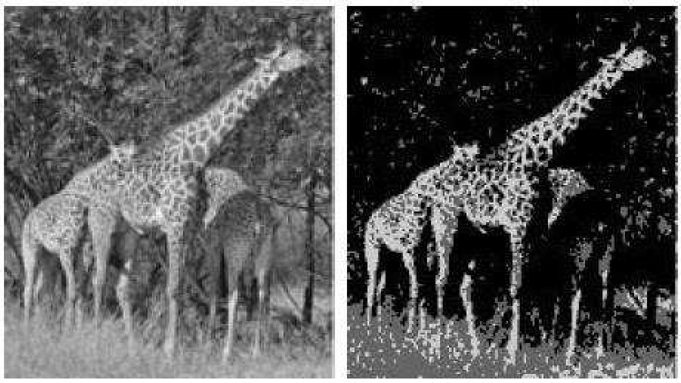

Figure 4. A difficult to segment pictures, with low contrast between the objects of interest (giraffes) and the background (savanna). For the original color and gray level picture, CopyRight 2012 by Berkovitch and [12].

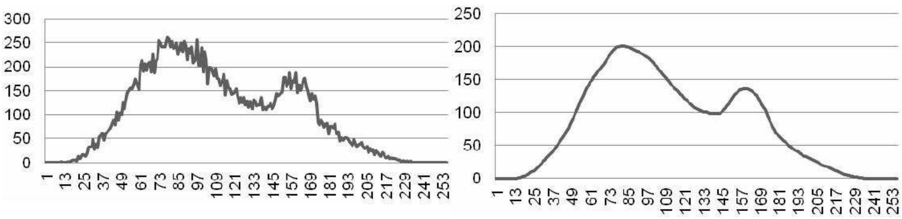

Figure 5. Original and smoothed histograms for the young giraffes picture

An example of result for the removing of bright reflectance spots is shown in Fig. 6, where the rule was applied without the condition on the area of the spots (direct application of the consequent of the rule whenever the object was bright.)

Notice that the procedure does not remove the gray contours of

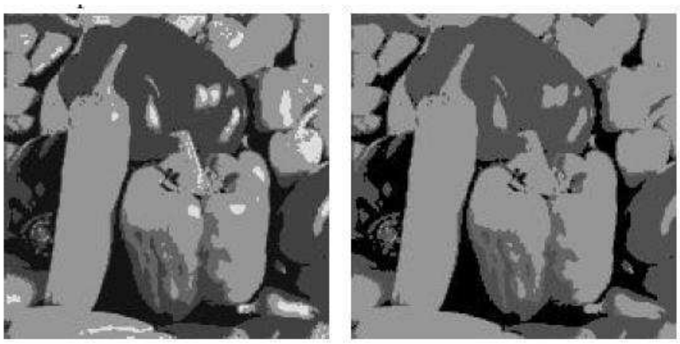

Figure 6. Removal of the reflection bright spot using the heuristic rule in the text

the bright spots. In another paper we will present a refinement of the procedure.

3.2 Indices of similarity

The visual comparison of the results produced by our method and by other method reported in the literature is time consuming and too subjective. There are several indices defined in the literature for assessing the results of segmentation [16], [15]. Most of these indices are based on counting the pixels that are common to the same segments in two segmented images (one of them being frequently segmented by a human operator), or on counting the number of pixels not in common to the corresponding segments. We defined a similar index as follows. To each object in an image, we associate the couple of values (S_k, O_j), or equivalently (k, j), where k is the number of the segment to which the object belongs, and j is the current number of the object in the segment S_k. For each object, we define the matrix $M_{k,j}^{[1,2]}$ with the same dimension as the image and with values 1 if the pixel belongs to the object, respectively 0 if it does not belong. For two segmentation results, we obtain the collection of matrices $A = \{M_{k,j}^{[1]}\}$ respectively $B = \{M_{k,j}^{[2]}\}$. First, assume that the number of segments is equal. We count the absolute difference of the corresponding matrices for objects in the two sets, A, B. When an object occurs in one set, but not in the other, the missing object is represented by a null matrix. Next, we count the sum of the elements of the difference matrices for all the objects. Let us denote it by Δ. Then, the dissimilarity index of the two segmentations is defined as $D_1 = \Delta / N_{pixels}$, where N_{pixels} is the total number of pixels in the image. When $D_1 < 0.05$, the segmented images are very similar with respect to this criterion. A second index easy to define and compute in the same procedure is the number of non-corresponding objects. For every null matrix defined in the above procedure, we increment a counter for counting the total number of such objects. Denote this number by N_n. Also, we count the total number of objects in the images (that is, the total number of matrices in A and B, including the non-corresponding objects), N_o. The second dissimilarity index is defined as $D_2 = N_n/N_o$.

When the number of segments is different in the two images, we need a different approach for comparing the segmented images. We work directly with objects, not taking into account the segments. The procedure is as follows. From one image, we select the greatest object (with the largest number of pixels) and determine the object that best matches it in the second segmented picture. For the pair of objects so determined, we compute the number of non-matching pixels, N_{n_1}. After removing the two objects, we iterate the same procedure until no objects remain unmatched. The sum of values N_{n_k} is denoted by N_n. The dissimilarity is then computed as above.

Code for dissimilarity:

```
read A[N][M], B[N][M], i,j;
read long delta=0, k;
begin for i=0:N-1
   begin for j=0:M-1
      delta+=abs(A[i][j] - B[i][j]);
   end for
end for
D1=delta/(N×M);
```

if D1 $\leq 5/100$ **Images are similar**
else **Images are not similar**

We exemplify the results of comparison of segmented images for the images with green peppers. The results are not similar in several respects. Because we have applied a correction by removing the regions strongly reflecting light, these regions are no more obtained as segments, which is an improvement. In addition, some shades and some darker regions are not determined as segments by our method, which in some cases is good.

4 Discussion

In every sub-segment (object), we compute the average of the gray level, the median, and the standard deviation. Also, for full characterization of the objects, the histogram of gray levels of the objects is computed. This information is used in the comparison of the objects in the image and in detection of sub-classes of objects, taking into account that objects from the same segment may differ in their type. Two objects are classified as of the same type if their histograms are similar.

Because segmentation is prone to noise, we need an extra phase of cleaning the segments by removing noise pixels and small sets of pixels that represent 'segmentation noise'. Average filtering is not an option, because averaging would change the gray level inside the segment. Instead, median filtering with a small window (3×3) is useful in removing isolated noise pixels inside the segments. Yet, the median filter can not remove all noisy pixels. We tested the following simple procedures after the application of the median filter.

Segment compaction procedure ♯1 If in the initial segmented image, in a 3×3 window that is totally embedded in the segment (that is, all neighboring pixels belong to the segment) there are up to two pixels not belonging to the segment, then they are converted to the segment.

Segment compaction procedure ♯2 Any object of at most 5 pixels completely surrounded by pixels of another segment becomes the surrounding segment.

Drawbacks of our methods are the need to pre-determine the procedure parameters δ and λ, or equivalently, δ and the number of segments. Also, the procedure of filtering the histogram is based on the first author experience and on experiments, namely the windows widths and the number of filtering stages being empirically chosen. The first drawback can be partly eliminated by imposing the number of segments and automatically adjusting the value of δ to obtain the number of segments. The second disadvantage can be eliminated by requiring a limited level of high frequency noise in the histogram and automatically tuning a filter to remove accordingly the noise. We will work out these improvements and show the results in another research.

5 Conclusions

We demonstrated a novel simple segmentation method based on a mixture of statistical and heuristic procedures. The method involves the selection of thresholds for the segments in a manner largely complementary to the well-known ‘valley’ method. In addition, the method uses a set of simple heuristic rules for further improving the segmentation. While the degree of novelty is limited to inversing the standard procedure based on the ‘valleys’ of the histogram and on adding a few features that improve the quality of the segmentation, the overall fabric of the algorithm undoubtedly brings novelty and improves results in case of some of the processed pictures.

The proposed segmentation procedure has the advantage of low computational requirements, making it suitable for small embedded systems and real-time applications. Further improvements regard the automation of the choice of the δ value and the filtering of the histogram.

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Authors' contributions. HNT proposed the topic, the method of solving the segmentation, the stages and main steps of the algorithms, some of the pictures for processing, interpreted most of the results and derived conclusions, wrote most of the paper, edited it (in LaTeX), and set in motion the writing of the code. MR wrote the code, performed simulations and experiments, contributed to the interpretation of the results, and contributed writing the paper.

Both authors agreed with the final form of the paper.

Annex

Histogram smoothing. The smoothing of the histogram is performed with the sequence of averaging and median (Med) filters:

$$n_1[k] = (1/11)Sum_{h=-5..+5}n_0[k+h]$$

$$n_2[k] = Med_{W_{h=-2..+2}}n_1[h+k]$$

For obtaining a smooth histogram we applied the average filter twice and then the median filter, using a window of 11 samples, respectively 5 samples (with centered pixel).

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