Adaptive Image Segmentation Based on Histogram Transition Zone Analysis

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Abstract

While segmenting “complex” images (with multiple objects, many details, etc.) we experienced a need to explore new ways for time-efficient and meaningful image segmentation. In this paper we propose a new technique for image segmentation which has only one variable for controlling the expected number of segments. The algorithm focuses on the treatment of pixels in transition zones between various label distributions. Results of the proposed algorithm (e.g. on the Berkeley image segmentation dataset) are comparable to those of GMM or HMM-EM segmentation, but are achieved with significantly reduced computation time.

Keywords: image segmentation, image analysis, comparative evaluation

1. Introduction

Image segmentation is the basis of efficient image analysis and data extraction. Image segmentation algorithms partition the input images into pairwise disjoint regions. Segmentation results (i.e. the segments) can be used for object proposals [1, 2] which may define candidates for a classification module. Image segmentation methods follow different strategies such as region-based [3], active contours [4], clustering [5], histogram-based [6], graph-based [7], or deep learning [8]. Histogram-based methods do not require any prior information about the input images, and date back to the beginning of image analysis [9]. This paper proposes a histogram-based algorithm (called *adaISA*) for adaptive image segmentation.

Given an image, the algorithm uses only one parameter for the segmentation; *adaISA* decides about this number by only analysing the histogram of image features. Our algorithm is applicable to both gray-level or colour images.

In general, considered features for image segmentation can be vectors combining (x, y) pixel coordinates, pixel values, or low-level descriptors such as local means, variances, or estimated gradient values. For example, SLIC [10] combines coordinates (x, y) and $L^a a^* b^*$ pixel values into 5-dimensional feature vectors, and mean-shift methods, e.g. discussed in [2], consider feature vectors defined by intensity values plus local means and variances. Feature vectors with $n \geq 1$ components define *n-channel images*; value distributions are commonly represented by *n*-dimensional feature histograms.

Our *adaISA* evolves from the common basic idea [9] that local minima in a feature histogram indicate border pixels between segments. Local minima in the histogram are basically at places where feature distributions intersect; *adaISA* pays special attention to the transition zones of feature distributions.

Received: Dec. 14, 2016

Revised : Dec. 19, 2016

Accepted: Dec. 22, 2016

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We tested our approach for various definitions of feature spaces, and decided finally to break down the analysis of multi-channel (feature) images into a subsequent analysis of single-channel images; we combine then the results achieved for the single channels. This leads to results comparable to state-of-the-art algorithms. We only have to deal with 1D histograms. *adaISA* does not consider feature vectors; instead we compute label images for single channels, and unify those into a single label image.

The paper is structured as follows. Section 2 specifies a basic single-channel *image segmentation algorithm* (ISA) for 1D histograms. This will then be refined in Section 3 into a Euclidean or Gaussian *adaISA* for a single channel; both versions are finally combined in Section 4 into Euclidean or Gaussian *adaISA* for multi-channel images. Section 5 provides qualitative and quantitative performance evaluation. Section 6 concludes.

2. A Very Basic 1-Channel ISA

Before discussing the proposed *adaISA* for multi-channel images, we start with a variant of a very basic adaptive ISA, similar to those histogram-based segmentation algorithms known from the early days of image processing [9].

The core idea of this basic 1-channel ISA can be easily summarised as follows: For every local minima i in any of the 1D histograms H of a multi-channel image, define a threshold τ_i at that position, then finish the scan of the respective histogram H by putting all the thresholds into a threshold vector $v_{th} = [0, \tau_1, \tau_2, \dots, \tau_N, 255]^T$, where N is the number of generated thresholds; for finding those we use Algorithm 1. Then merge the segment channels in a final segmented image; see Section 4.

The chosen basic ISA does not perform local derivations of the 1D histogram for trying to find zeros at extrema (and for checking whether there is actually a local maxima or a local minima). Instead, the used basic ISA simply scans the whole histogram and finds local minima initiated by available global information.

First, this basic ISA applies a (small) mean filter to the histogram H which is the convolution $H_f = H * K$ between H and the kernel $K = [0.50.5]$. Then it considers the filtered histogram H_f .

Second, this basic ISA scans the histogram with a *scan line* defined by a series of adjacent elements and checks whether there is a local minimum value in the considered interval. The

Algorithm 1 Local minima by a basic ISA

```

1: Inputs:  $n, H$  {size of scan line}.
2:  $v_{th} = [\emptyset]$  {threshold vector starts as empty array}.
3:  $H_f = H * 1/2[1, 1]$  {smooth the histogram  $H$ }.
   {Note: after the convolution,  $H_f$  and  $H$  must be of equal
    $length(H_f) = length(H)$ }.
4: for  $x_1 = n$  to  $length(H_f) - n$ :
5:    $h_{lower} = [\emptyset]$  {starts as an empty array},
6:    $h_{upper} = [\emptyset]$  {starts as an empty array}.
7:   for  $x_2 = 1$  to  $n$ :
8:      $h_{lower} = [h_{lower}, H_f(x_1 - x_2)]$ ,
9:      $h_{upper} = [h_{upper}, H_f(x_1 + x_2)]$ .
10:  end for
11:   $h_{complete} = [h_{lower}, h_{upper}]$ ,
12:  check whether  $H_f(x_1)$  is the minimum value in the
    $h_{complete}$  array.
13:  if  $(\sum_{p=1}^{2n} h_{complete} > H_f(x_1)) = 2n$  :
14:     $v_{th} = [v_{th}, x_1]$ .
15:  end if
16: end for
17:  $v_{th} = v_{th} - 1$ .
18:  $v_{th} = [0, v_{th}, 255]$ .
19: Output:  $v_{th}$ 

```

number of detected local minima is at this stage proportional to the size $2 \times n$ of the considered scan line, where n is the only parameter of this basic ISA and is the half of the size of the scan line.

The basic ISA starts with two empty arrays h_{lower} and h_{upper} which are filled with the values corresponding to lower and upper values in the scan line. Algorithm 1 is the pseudocode of the used basic ISA. Note that the pseudo code has a similar notation as known from MATLAB.

At the end of Algorithm 1, v_{th} is decremented by one since the histogram H is a vector with 256 elements, where the index goes from 1 to 256, but the threshold must have a value between 0 and 255. This basic ISA has $n > 0$ as its only parameter.

3. Adaptive ISA with Transition Zones

Transition zones of value distributions have been considered in various histogram-based ISAs, such as Otsu binarization [6] or the Gaussian mixture model (GMM) [12]. These methods aim at optimising a threshold under particular assumptions. The main problem of such algorithms is that a calculated threshold is not flexibly applied: A pixel with a given value can only belong to a segment defined by the pixel's value position relatively to the given threshold. We turn Algorithm 1 now into an *adaptive* ISA by providing a flexible decision for pixels in the transition

Figure 1. A histogram with a transition zone near τ .

zones.

3.1 Strategy for Transition Zones

Transition zones are the areas of the histogram that enclose a threshold; see Fig. 1. In these zones, pixel values are not defining a unique assignment to one of the two adjacent peaks in value distributions. The size of the transition zone is defined by n , where the transition zone extends from the threshold position τ of the histogram and goes n elements to the left of τ , and n elements to the right of τ . The red zone and the orange zone are divided by threshold τ . In the shown case we have a transition zone of size $2 \times n$. The assumed width of transition zones defines parameter n in the basic ISA (i.e. Algorithm 1).

We want to identify pixels with values in these transition zones. For those pixels we decide to which of the two adjacent peaks they should actually be assigned to (and not only by simply applying the threshold at the given valley).

Pixels that contribute to the transition zone will be assigned individually to either the red segment or the orange one shown in Fig. 1, depending on “which segment is closer”. We propose two methods for measuring “close”, either by computing the Euclidean distance or by computing the probability using Gaussian distributions for values in the considered image channel.

3.2 Use of Euclidean Distance

We consider a 3D feature space, defined by pixel position (x, y) and the selected single channel value for $I(x, y)$, for the given image I . First we compute the centroid (in this 3D feature space) of all the pixels which contribute to one of the two histogram segments that are to the left or right of the threshold. In the example of Fig. 1, we compute one centroid for the red segment, and one for the orange segment. Then we compute for

each pixel $(x, y, I(x, y))$ with an assigned value in the transition zone the Euclidean distance

$$\sqrt{[I(x, y) - \mu_1]^2 + [x - \mu_2]^2 + [y - \mu_3]^2}, \quad (1)$$

in the relevant 3D feature space to those two centroids, and assign it to segments defined by the closer centroid.

Assume that we have N_{segments} clusters (or peaks) defined by the considered channel (i.e. the given 1D histogram H). Then, we need to consider N_{segments} centroids defined by $\mu_{\alpha 1}$, the mean channel value of cluster α , $\mu_{\alpha 2}$, the mean x -value of pixels that belong to cluster α , and $\mu_{\alpha 3}$, the mean y -value of pixels that belong to cluster α , with $\alpha \in \{1, 2, \dots, N_{\text{segments}}\}$. N_{segments} is the number of thresholds obtained by Algorithm 1 plus one.

3.3 Use of Gaussian Distributions

In this case we model segments by Gaussian distributions that depend on the 1D channel values of the pixels and their positions (x, y) . In the example of Fig. 1, we sketch two Gaussian distributions, a red one and an orange one.

For every pixel inside of the transition zone we compute the probability to be part of one of the two “adjacent” Gaussian distributions. The pixel is then assigned to the segment with the Gaussian distribution where it has a higher probability to belong to. The Gaussian distribution is here of the form

$$\frac{1}{(2\pi)^{n/2} |\Sigma_\alpha|^{1/2}} e^{-\frac{1}{2} [\mathbf{x} - \mu_\alpha]^\top \Sigma_\alpha^{-1} [\mathbf{x} - \mu_\alpha]}, \quad (2)$$

where $\mathbf{x}$ is the vector that contains the 3D information of the pixel $(I(x, y), x, y)$ (i.e. its channel value and coordinates x and y), α is the label of the segment defined by $\alpha = \{1, 2, \dots, N_{\text{segments}}\}$, where N_{segments} is the number of segments, Σ is the covariance matrix, and μ the mean vector.

4. adaISA for Multi-Channel Images

We specify the proposed algorithm *adaISA* now for multi-channel (or multi-feature) images. We discuss a 3D image-value example, which is easy to generalise for any multi-channel situation. For images in *Lab* space, we apply the single-channel method individually, for each colour channel L^* , a^* , and b^* , which are the input images of Algorithm 1. We obtain label images Ψ_L , Ψ_a , and Ψ_b , which are the output images of Algorithm 1.

We unify those by applying Algorithm 2. First, we merge the

Algorithm 2 Multi-Channel Images

- 1: Inputs: Ψ_a, Ψ_b, Ψ_L { channels of the label image }
- 2: $\Psi_{color}(x, y) = [\min(\Psi_a, \Psi_b) - \max(\Psi_a, \Psi_b)](x, y)$,
- 3: $\Psi(x, y) = [\min(\Psi_{color}, \Psi_L) - \max(\Psi_{color}, \Psi_L)](x, y)$.
- 4: Output: $\Psi(x, y)$

label images of both color channels Ψ_a and Ψ_b into one label image Ψ_{color} representing information of the color channels. Then we merge Ψ_L with Ψ_{color} to generate the label image Ψ . This basic algorithm avoids any loops or iterations, and any complex operations. The performance of adaISA is very fast and allows us to obtain consistent results.

This algorithm is a modification of the *blending Phoenix algorithm* [11].

5. Results of the Proposed Adaptive ISA

We present results of the two versions of adaISA by using for transition zones either the Euclidean distance or Gaussian distributions. Input images are in *Lab* space.

We compare both versions of adaISA with two common image segmentation algorithms based on the *Gaussian mixture model* (GMM) [12], or the *hidden Markov model with expectation maximisation* (HMM-EM) [13].

5.1 Rand Index Criterion

We evaluate similarity of results by using the *Rand index criterion* [14]. This criterion can be used for measuring the similarity between two label images Ψ_1 and Ψ_2 of identical size; normally we take Ψ_2 as the ground-truth image. Algorithm 3 follows Equ. (3) in the algorithm; it shows the steps for calculating this measure $\mathcal{R}(\Psi_1, \Psi_2)$, expressing the similarity between Ψ_1 and Ψ_2 in percent.

5.2 Size of Transition Zones and Resolution of Segmentation

We test adaISA using different values of parameter n . Figure 4 shows input image El Castillo Stitch 2008⁴ and results of the Gaussian adaISA for $n = 17$ and $n = 9$. Figure 3 shows the input image Michoacan⁵ and results of the Euclidean adaISA for $n = 3$ and $n = 10$. Figure 3 shows the input image Fountain, also from the CCV data set, and

Algorithm 3 Rand Index Algorithm

- 1: Inputs: Ψ_1, Ψ_2 { label images }
- 2: $L = \text{zeros}(\text{width}, \text{height})$ { histogram }.
- 3: **for** $i = 1$ **to** width :
- 4: **for** $j = 1$ **to** height :
- 5: $l_1 = \Psi_1(i, j)$,
- 6: $l_2 = \Psi_2(i, j)$,
- 7: $L(i, j) = L(l_1, l_2) + 1$.
- 8: **end for**
- 9: $l = \sum_i \sum_j L(i, j)$ {sum all the elements, width,height}.
- 10: $u = \sum_i L(i, j)$ {sum over the horizontal direction, width}.
- 11: $v = \sum_j L(i, j)$ {sum over the vertical direction,height}.
- 12: $r = 1 - 2 \frac{(u \cdot u^T) + (v \cdot v^T) - 2 \sum_i \sum_j L(i, j) \times L(i, j)}{l(l-1)}$,
- 13: $\mathcal{R} = r \times 100$.
- 14: Output: $\mathcal{R}$

Figure 2. Left: Original image El Castillo Stitch 2008. Middle: Gaussian adaISA for $n = 17$. Right: Gaussian adaISA for $n = 9$

Figure 3. Left: Original image Michoacan. Middle: Euclidean adaISA for $n = 3$. Right: Euclidean adaISA for $n = 10$

Figure 4. Left: Original image Fountain. Middle: Gaussian adaISA for $n = 7$. Right: Gaussian adaISA for $n = 3$

results of Gaussian adaISA with $n = 7$ or $n = 3$. All three input images are here shown as examples for “complex” scenes, showing diverse objects in structured environments,

Smaller values for $n > 0$ produce in general a larger number of segments. Figure 2 is still too simple in structure for a good illustration of this effect.

In Fig. 3, $n = 3$ allows us to subsegment the faces and the

⁴Image in public domain, see <https://commons.wikimedia.org>

⁵From the CCV data set, publically available at ccv.wordpress.fos.auckland.ac.nz/data/single-images/

drawings on the dresses, and even the flag at the top of the building in the background, and $n = 10$ produces just three segment categories; for example, floor and legs of the people are in the same segment category.

Figure 4 shows that information on the left (front of buildings) is lost for Gaussian *adaISA* with $n = 7$, but $n = 3$ allows us to assign segments to individual windows in this region. Parameter n , the only input parameter of our code, controls the resolution of the segmented image.

5.3 Results and Comparison with Other Approaches

In this section we apply *adaISA* with Gaussian distributions to the images of the Berkeley data set. In comparison, we also run methods based on GMM and HMM-EM on these images.

Table 1 lists Rand indices for estimating the similarity between results and the ground truth. For *adaISA*, the first column compares the Gaussian *adaISA* with ground truth *adaISA*, while the second column and the third column compares the GMM and HMM-EM with the ground truth, respectively.

Rand indices on the Berkeley data set demonstrate similarity between results obtained by Gaussian *adaISA*. Because *adaISA* has only a significant impact on pixels in transition zones, it is also no surprise that results for Gaussian *adaISA* are very similar to those obtained by HMM-EM segmentation.

From Table 1 we compute the mean, the standard deviation, the maximum value, the minimum value, and the median of the results for every code. Those values are presented in Table 2.

Figure 5 presents a gallery of resulting images when Gaussian *adaISA* is applied to images of the Berkeley data set. The first column shows original images, the second shows segment-border images, and the last column shows maps of labels of segment categories.

Figure 6 presents a gallery of resulting label maps for Gaussian *adaISA*, GMM segmentation, or HMM-EM segmentation for some of the images of the Berkeley data set. The first column shows (in gray-levels) label maps for the Gaussian *adaISA*, the second column (in blue colors) GMM label maps for, and the third column (in red colors) HMM-EM label maps. Euclidean *adaISA* is not shown in this gallery in Fig. 6 due to available space, but results of Gaussian or Euclidean *adaISA* are similar.

Figure 7 presents a gallery of resulting images when Gaussian *adaISA* is applied to images of the Berkeley data set. The first column shows original images, the second shows ground truth images, and the last column shows maps of labels of segment categories.

Table 1. Rand indices for some of the images of the Berkeley data set. See text for explanation.

Image name	ISA%	GMM%	HMM-EM%
# (167062)	91	83	92
# (42049)	83	78	88
# (62096)	90	83	89
# (101085)	82	84	82
# (241004)	93	87	90
# (37073)	89	82	84
# (296059)	86	72	89
# (145086)	89	85	91
# (119082)	79	64	78
# (208001)	81	76	85
# (189080)	76	68	83
# (160068)	84	77	89
# (147091)	92	91	90
# (3096)	84	76	82
# (302008)	71	73	72
# (86016)	93	83	80
# (24077)	70	78	74
# (198023)	91	72	80
# (181079)	86	78	84
# (198054)	83	71	84
# (135069)	90	80	87
# (388016)	74	75	83
# (182053)	80	81	81
# (2100)	70	73	70
# (21077)	90	86	87
# (376043)	88	68	83
# (106024)	72	67	77
# (302008)	71	70	79
# (197017)	82	80	83
# (299086)	80	81	80
# (241048)	91	82	87
# (65033)	85	80	90
# (351093)	82	80	84
# (361010)	83	81	86
# (8068)	81	83	90
# (3063)	94	80	90
# (181021)	86	81	84

Figure 5. Resulting gallery of using Gaussian adaISA for some of the images of the Berkeley data set.

Table 2. Statistics of results for the images of the Berkeley data set of Table 1

Variable	ISA%	GMM%	HMM%
mean	82.4	78.08	83.97
std	7.15	6.13	5.36
min	70	64	70
max	94	91	92
median	84	80	84
average run-time	0.89 sec	9.78 sec	88.7 sec

Figure 6. Gallery Left column: Gaussian adaISA , Center column: GMM Right column: HMM-EM.

5.4 Segmentation of Aerial Images

Our interest in segmentation is motivated by aerial image analysis, and we show finally a few examples from this area of application.

Figure 8 shows the bay of Cancun; the image `Landsat_Cancun_Mexico` is available in the Wikimedia Commons data base. We illustrate in the figure that adaISA can segment independently the main regions of the bay such as the deeper ocean, the coast, the jungle, weed, the infrastructure, and also some boats on the ocean. The original image is on the left in the figure, the segment-border image is in the middle, and the label map on the right. We used Gaussian adaISA with $n = 5$.

Figure 9 shows also an image from Wikimedia, the eruption

Figure 7. Gallery *Left column*: Original images , *Center column*: Ground truth images *Right column*: Gaussian adaISA.

Figure 8. *Left*: Original Landsat Cancun Mexico from Wikimedia commons database. *Middle*: Segment-border image. *Right*: Label map

of the Calbuco volcano. Gaussian adaISA with $n = 12$ can easily segment the cloud of dust and ashes of the volcano and thus compute the area affected by the eruption.

Figure 10 shows an image from Wikimedia of a dust storm

Figure 9. *Left*: Original Eruption_of_Calbuco_volcano from Wikimedia commons database. *Middle*: Segment-border image. *Right*: Label map

Figure 10. *Left*: Original Dust_storms_off_southern_Argentina from Wikimedia commons database. *Middle*: Segment-border image. *Right*: Label map

in southern Argentina. Gaussian adaISA with $n = 3$ was used to segment the image to measure the area covered by the dust storm. This input example is harder than the image of the Calbuco volcano since it is even hard for the human eye to identify the dust. The program was even identifying the dust in the lower part of the image.

The three examples illustrate the sensitivity of the proposed segmentation method if regions of only very vague value differences need to be split into different segment categories.

6. Conclusions

We proposed with adaISA a novel adaptive image segmentation algorithm. It is a fairly straightforward extension of common histogram-based image segmentation strategies. The proposed algorithm segments images without any prior information about the image or the number of intended segments. The user can finally decide about the number of used thresholds, for every image of processed video data, or for whole classes of images at once.

Our tests show that Gaussian adaISA can be a good competitor for GMM and HMM-EM segmentation, with the advantage that adaISA requires less operations, is easier to program, and

is deterministic while GMM and HMM-EM are not.

What makes *adaISA* special is that it follows simple concepts and applies a minimised number of steps; thus it significantly decreased computational time complexity compared to other segmentation methods while leading to comparable results. In other words, the main contribution of this paper is that the proposed algorithms lead to results similar to those obtained by HMM or GMM, but with reduced time.

The algorithm applies to any multi-channel case. For example, it can also be used for *6D vision* [15] where depth and optic flow contribute to the definition of the used feature space.

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