

# Quality Analysis of Image Segmentation based on G-UN-MMS

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**Abstract** — We analyze the quality of segmentation of the simple segmentation algorithm based on G-UN-MM representation method introduced in other papers; then, we compare the segmentation results according to the G-UN-MMS with those obtained by other algorithms. We briefly present a preliminary report on the comparison of segmentation methods using only two objective comparison indices. Results that are more detailed will be presented in a definitive paper to extend this preliminary one.

**Index Terms** —image segmentation, G-UN-MM models, segmentation quality, unsupervised evaluation

## I. INTRODUCTION

Image segmentation is the separation/delineation of objects between them and against background. There is a lot of segmentation methods in literature such as: region-growing [1], [2], split and merge [3], clustering method: k-means, fuzzy C-means [4], edge-based segmentation [5] thresholding [6], [7] as well as other segmentation methods [8] based on combination of the above. Therefore, the quality of segmentation, the similarity of the results with segmentation by human operators should be evaluated. Quality can be determined subjectively by human assessors, or objectively, by computer using quantitative indicators (factors). When comparing methods by the machine, the empirical factors are modeling the quality assessment made by the experts.

Carrying out an unsupervised segmentation means excluding the human factor and using metrics indicating the quality of segmentation. One metric of quality is precision boundary object / objects against the background. A difficult case is, for example, the delineation of small objects (coffee beans, peas, etc.) that could be considered texture.

Of concern in segmentation is the accuracy of the segment assessment – checking whether the segment is equal to the surface area of the object in the image area; for example, reflections of light and shadows are often determined as separate segments.

Yet another characteristic evaluated for segmentation algorithms is the computational complexity (computational complexity of time and space).

## II. UNSUPERVISED EVALUATION OF SEGMENTATION METHOD

When making supervised evaluation, the segmentation results are compared with those of stereotyped ones provided by experts in the field: the experts are drawing the outline of objects, manually delimiting the area of interest to be further processed. In

case of unsupervised evaluation, several evaluation metrics were proposed for assessing the homogeneity of the regions, the difference of the mean value between regions, the contrast between object and the background region, to decide if too many or too few segments are obtained and others [9], [10], [11]. An important factor in evaluating the quality of segmentation is the texture. Test images for this work do not contain textures, but the texture-based segmentation is widely used [12]; moreover, texture features combined with other methods improve the determination of texture regions [13].

In order to decide if an over-segmentation has occurred, i.e. if there are more segments than actually objects in the image, J. Liu and Y.-H. Yang [14] have proposed the following function:

$$F(I) = \sqrt{N} \sum_{j=1}^N \frac{e_j^2}{\sqrt{S_j}} \quad (1)$$

where  $I$  is the segmented image,  $N$  is number of obtained regions after segmentation,  $S_j$  – area of region  $j$  and  $e_j^2$  – squared color error (or the gray level) that is calculated as

$$e_j^2 = \sum_{k \in S_j} (x_k - \bar{x})^2 \quad (2)$$

where  $x_k$  is the gray level of the pixel, and the  $\bar{x}$  means gray level of the region. Therefore  $e_j^2$  shows the scattering of the gray values of pixels on a surface. In order to calculate the correct variance, it is required to include in the computation the surface area (total number of pixels in the region  $S_j$ ) the gray values are distributed on. For regions with an uniformly distributed gray value, we obtain  $e_j^2 = 0$ .

### III. SEGMENTATION ALGORITHM BASED ON G-UN-MMS

The segmentation methods based on histogram usually determine the thresholds as being the minimum values of the histogram – the “valleys” of Gaussian distribution. We, HN.Teodorescu and I, have proposed a novel way of using the global statistics of gray images for image segmentation. [15]. 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. These are the intervals  $X_k$  satisfying one of the sets of conditions  $\forall x_1, x_2 \in X_k \quad |p(x_1) - p(x_2)| < \delta$  and  $length(X_k) > \lambda G_{max}$ ,  $0 < \lambda < 1$ , with  $\delta$  and  $\lambda$  predetermined parameters of the procedure, or  $\forall x_1, x_2 \in X_k \quad STDV(X_k) < \delta$  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 segments of the image  $G(i, j)$  are determined according to the

intervals  $X_k$  so determined. By varying the parameters  $\delta$  and  $\lambda$ , several segmentation results can be obtained.



a. peppers                      b. Lena  
Fig. 1 Typical test images: *peppers* [16] and *Lena* [17]

### IV. RESULTS

The results achieved on test images “*peppers*” and “*Lena*” from [16] respectively [17] that we used in our previous works [15] and [18] are given in Table I. For comparing the results, we have chosen the Otsu standard method [20], which is also a segmentation method based on histogram.

For the test images *blood cells* [21] and *rice* [22] we compute the *inter-region disparity metric*  $\sigma_B^2$  [23].

TABLE I. SEGMENTED IMAGES WITH THE PROPOSED METHOD AND OTSU’S METHOD (WITH 2 THRESHOLDS), DISPERSIONS VALUES FOR SEGMENTS AND ORIGINAL IMAGES, FUNCTION F

Segmented image with <b>proposed method</b>			
$S_1=22.24 \quad S_1/S_{im}=0.41$ $S_2=6.95 \quad S_2/S_{im}=0.13$ $S_3=23.87 \quad S_3/S_{im}=0.44$ Simage=54.31 <b>F=216 562</b>	$S_1=25.92 \quad S_1/S_{im}=0.57$ $S_2=6.98 \quad S_2/S_{im}=0.15$ $S_3=20.94 \quad S_3/S_{im}=0.46$ Simage=45.73 <b>F=215 677</b>	$S_1=34.70 \quad S_1/S_{im}=0.72$ $S_2=10.94 \quad S_2/S_{im}=0.23$ Simage=48.26 <b>F=241 308    <math>\sigma_B^2 = 1825</math></b>	$S_1=7.61 \quad S_1/S_{im}=0.14$ $S_2=42.51 \quad S_2/S_{im}=0.78$ Simage=54.32 <b>F=337 360    <math>\sigma_B^2 = 2425</math></b>
Segmented image with <b>Otsu’s method</b>			
$S_1=21.44 \quad S_1/S_{im}=0.40$ $S_2=17.63 \quad S_2/S_{im}=0.32$ $S_3=19.08 \quad S_3/S_{im}=0.35$ <b>F=195 039</b>	$S_1=12.16 \quad S_1/S_{im}=0.27$ $S_2=18.06 \quad S_2/S_{im}=0.40$ $S_3=21.29 \quad S_3/S_{im}=0.47$ <b>F=161 258</b>	$S_1=14.08 \quad S_1/S_{im}=0.30$ $S_2=22.10 \quad S_2/S_{im}=0.46$ <b>F=154 203    <math>\sigma_B^2 = 1916</math></b>	$S_1=17.05 \quad S_1/S_{im}=0.31$ $S_2=32.34 \quad S_2/S_{im}=0.60$ <b>F= 234 402    <math>\sigma_B^2 = 2518</math></b>

Here,  $s_1, s_2$  and  $s_3$  represent the gray values of the segments,  $S_1, S_2, S_3$  - the dispersion of the segments. The segmented images by Otsu method were obtained by us using the algorithm from [20].

One of the metrics for evaluating the quality of binary images segmentation is inter-region disparity:

$$\sigma_B^2 = \frac{S_B}{S_I} \cdot \frac{S_O}{S_I} \cdot (\bar{x}_{k(O)} - \bar{x}_{k(B)})^2 \quad (3)$$

where  $S_B$  is the areas of the background and  $S_O$  - the area of the object,  $\bar{x}_{k(O)}$  and  $\bar{x}_{k(B)}$  represent the average values of the gray-level of the object and respectively of background.

The proposed algorithm [15] for histogram segmentation uses at least two thresholds (the limits of the largest quasi constant interval on the histogram). For obtaining a segmented binary image was chosen for "blood cells" the right limit as threshold (Th2) and for "rice" - the left (Th1). Otsu algorithm provides the number of obtained classes at beginning (1 ... n), and finds k thresholds for effective segmentation based on determining a smaller dispersion within the classes.

Evaluation of a segmentation method can be performed by comparing the results with those achieved by using standard segmentation algorithms (reference algorithms). We chose to compare the achieved results with K-Means clustering segmentation method, as described in [19] and one of the versions of Otsu method, as described in [20].

Notice that the gray value we used for the segments are not necessarily identical with those used in the

literature for the same images. The function F and the inter-region disparity metric  $\sigma_B^2$  are calculated on the gray-level of the original images. The gray-level of the represented segments has no influence on the obtained results.

In order to make a comparison of the results of *peppers* color image segmentation [24] by using the proposed method with other methods from the literature, we take into account primarily the number of obtained segments. Using different comparison values in the G-UN-MM algorithm for determining the constant intervals upon the color image segmentation (the application of segmentation algorithm on each array separately: Red, Green and Blue) we have got different numbers of segments, as in Table III.

TABLE II. NUMBER OF OBTAINED SEGMENTS

Comparison value for determining the threshold	Number of segments
p=1.5	3
p=3.5	6
p=5.0	8

For comparing the results we chose the representation of obtained segments surfaces intersections: the proposed method with K-mean, the proposed method with Otsu and, finally, K-mean with Otsu.

TABLE III. SURFACES OF OBTAINED SEGMENTS

The method applied on image 'peppers.jpg' 410x410 pixels	Area in pixels and %					
	Segment 1		Segment 2		Segment3	
Color-Based Segmentation Using K-Means Clustering	48 470	28.83%	83 840	49.88%	35 790	21.29%
Image segmentation using Otsu thresholding	60 289	35.86%	77 303	45.99%	30 508	18.15%
Segmented Image with proposed method p=1.5	75 963	45.19%	88 633	52.73%	3 504	2.08%

TABLE IV INTERSECTION OF AREAS OF SEGMENTS

The method applied on image 'peppers.jpg' 410x410 pixels	Intersection of areas of segments Segmented Image with proposed method p=1.5					
	Segment 1		Segment 2		Segment 3	
Our Methods AND Color-Based Segmentation Using K-Means Clustering	48102	our 75 963	81220	our 88 633	3473	our 3 504
	28.61%	45.19%	48.32%	52.73%	2.06%	2.08%
Our Methods AND Image segmentation using Otsu thresholding	48773	our 75 963	77134	our 88 633	3487	our 3 504
	29.01%	45.19%	45.89%	52.73%	2.07%	2.08%
K-Means Clustering AND Otsu thresholding	36 296	kmeans 48 470	70 872	kmeans 83 840	18 561	kmeans 35 790
	21.59%	28.83%	46.16%	49.88%	11.04%	21.29%
		otsu 60 289		otsu 77 303		otsu 30 508
		35.86%		45.99%		18.15%

In Table IV the areas of the segments are in pixels. The values in % represent the number of pixels of the intersection of the corresponding segments vs.

$$100 \cdot \frac{\text{Nr. of pixels intersection}}{\text{Total Nr. of pixels in the image}}$$

For each segment, the first sub-column represents the area (in pixels) of the intersection of the segment obtained with the G-UN-MM

method with the corresponding segment obtained by the alternative method.

The intersection of areas of segments obtained with the proposed method and other methods:  $A \cap B = 50$  (black - color value 50),  $A - B = 100$  (gray - color value 100),  $B - A = 200$  (gray - color value 200), where A denotes segments obtained with proposed method, B - segments obtained using K-Means (a), respectively using Otsu thresholding (b)

TABLE V INTERSECTION OF AREAS OF OBTAINED SEGMENTS WITH PROPOSED METHOD AND K-MEANS CLUSTERING, OTSU'S METHOD

Segment 1	Segment 2	Segment 3
a. Intersection of areas of segments for Color-Based Segmentation using K-Means Clustering method		
b. Intersection of areas of segments for Image segmentation using Otsu thresholding method		

TABLE VI INTERSECTION OF AREAS OF OBTAINED SEGMENTS WITH K-MEANS CLUSTERING AND OTSU-S METHOD

Segment 1	Segment 2	Segment 3
Intersection of areas of segments using K-Means Clustering method and using Otsu thresholding		

The intersection of areas of segments of segmented image with proposed method and other methods:  $A \cap B=50$  (black - color value 50),  $A-B=100$  (gray- color value 100),  $B-A=200$  (gray- color value 200), where A denotes segments obtained from a specified image using K-Means and B denotes the same segments obtained from the same specified image using Otsu thresholding.

### V. CONCLUSIONS

According to the criterion of efficiency, the proposed method is a simple one, having a minimal resource consumption and fast computation. The results achieved are numerically close to those obtained with more complex methods [6], [25], [26]. Therefore, we conclude that the method is effective and satisfactory. The quality of the results indirectly validates the use of the model of mixtures of Gauss and Uniform Noises (G-UN-MM) proposed in our previous papers.

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