THRESHOLDING METHODS AND QUANTITATIVE EVALUATION OF RESULTS

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INTRODUCTION

Segmentation represents division of the image into uniform regions according to certain criterion. This step is important in image processing and usually monitors extraction, detection or recognition of objects. Formed image regions are called segments and they represent separate objects from the background.

The performance of segmentation is influenced by quality of the image and of the scene complexity. A good segmentation occurs when objects in the image have well defined contours and do not present shadows or reflections of light. These effects lead to bad results in image segmentation, especially those represented in gray levels. The color images have advantage to include as segmentation criterion the factor of color.

1. USUAL METHODS OF IMAGE SEGMENTATION

Depends on image quality and their complexity we choose a specific segmentation algorithm. In some cases, before segmentation algorithm is applied, an improvement of quality may required (achieve higher contrast and better enhancement of contours).

In the specialized literature we can find many kinds of color (or grayscale) image segmentation techniques, which can be grouped into four main categories:

1. ***Pixel based segmentation*** – a region is defined as a set of pixels that have similar intensity / color.
   - *histogram based techniques* [1-3];
   - *clustering techniques* [4];
   - *Fuzzy clustering techniques* [5-7].
2. ***Region based segmentation.*** The methods for detection of regions are based on similarity and spatial proximity between pixels. We know:
   - *the region growing techniques* – choose a pixel position and looking in the 8 directions if neighboring pixels corresponding to a criterion of similarity, forming homogeneous regions [8-9];
   - *the splitting and merging algorithms* [10] – the purpose is to divide the image in regions. Each
   - region, according to a certain sense is homoge-neous, but the concatenation of two adjacent regions is not homogeneous with the same sense.
3. ***Edge based segmentation*** [11, 12] – when a region is defined as a set of pixels defined by a color contour. For contour determination is important the change rate of gray levels (or color values of pixel).
4. ***Hybrid segmentation techniques*** [13-15] – improve the results of the segmentation by addition and / or combination of the above methods.

In the literature we found other techniques, such as those based on graphs [16]; special algorithms have been adapted to segmentation techniques using neural networks [17], Markov models, algorithms based on texture, color and other.

To apply a method or another depends on:

– the nature of image: capture mode, resolution, lighting, noise level

– the type of useful information (textures, text & etc..)

– the purpose of segmentation: location object recognition forms, interpretation, quality control, diagnostics & etc..

– the characteristics that must be extracted also influence the choice of segmentation methods: contours, regions, shape and texture.

An irregular lighting negatively affects the segmentation results, especially in methods based on the histogram. Also the presence of *salt and pepper* noise negatively affects the segmentation results and requires some preprocessing before applying segmentation methods.

For the gray images is indicated to use the histogram based segmentation, for the color images – the regions based segmentation. The method for edges detection can be implemented for both type of image: in grayscale and color.

2. SEGMENTATION METHODS BASED ON HISTOGRAM

The method described in previous works [18-19] is part of the segmentation methods based on pixel classification depending on their intensity.

The segmentation techniques based on histogram calculates the pixel values frequency. These techniques are based on thresholding of histograms and are effective when there is a relatively clear separation of pixel values between analyzed objects. In this case the given range of color represents a single class of objects.

Thresholding method consists in choosing an *N* number of thresholds: $Th_1, Th_2, \dots Th_N$ and create an labeled image, based on the original image, as follows:

if $g(i,j) <= Th_1$
  then $g(i,j) \in$ $segment_1$
if $g(i,j) > Th_1$ && $g(i,j) <= Th_2$
  then $g(i,j) \in$ $segment_2$
…
if $g(i,j) > Th_{N-1}$ && $g(i,j) <= Th_N$
  then $g(i,j) \in$ $segment_{N-1}$
if $g(i,j) > Th_N$
  then $g(i,j) \in$ $segment_N$

where $g(i,j)$ – the value of pixel, $segment_1$ - $segment_{N-1}$ – the objects in the image.

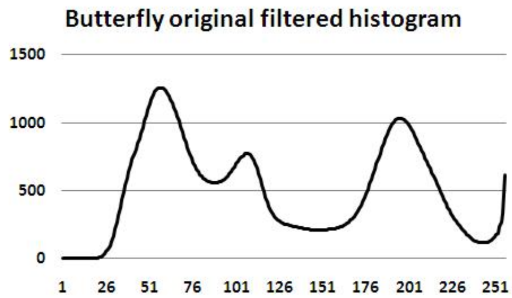


Figure 1. Example of the filtered histogram (image *butterfly* [20]).

On this histogram mentioned three well-defined peaks, therefore have two thresholds. Applying the Otsu method described below we achieved Th1=69 and Th2=141.

Figure 2. Original image *butterfly* [20] and segmented image (3 segments).

One of the reference segmentation methods on the histogram is Otsu's method. This method aims minimizing the intra-class variance. By default, the method is designed for image binarization, so obtaining of two classes (object and background), but the method can be adapted to obtain several classes.

Regions with a high homogeneity have low variance. For each threshold T (from 1 to 255) is calculated:

$$\sigma_W^2(t) = q_1(t)\sigma_1^2(t) + q_2(t)\sigma_2^2(t),$$

where t – the determined threshold, σ_i^2 – the variance of respective classes, $\sigma_W^2(t)$ – the weighted sum of variances of the two classes; $q_1(t)$ and $q_2(t)$ are the probabilities of the two separate classes by the threshold t and are determined as the sum of the probability that the pixels of a class are a certain intensity (gray level) on the specified interval (from 1 to t for the first class and from t to the highest intensity – for the second):

$$q_1(t) = \sum_{i=1}^{t} P(i) \text{ and } q_2(t) = \sum_{i=t+1}^{I} P(i), \qquad (1)$$

An implementation of Otsu's method can be found at http://www.mathworks.com/matlabcentral/fileexchange/26532-image-segmentation-using-otsu-thresholding/content/otsu.m.

t=85 t1=71, t2=136
a. b. c.

Figure 3. a) Test image *blood cells* [21]; b) binarized image (segmented with one threshold); c) segmented image with two thresholds (three segments).

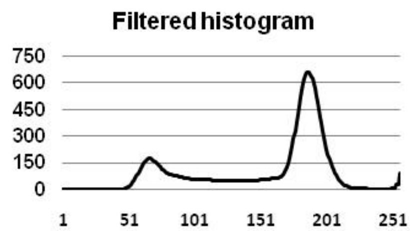


Figure 4. Filtered histogram of *blood cells* [21].

Many of the methods based on histogram, mentioned in the literature, refer to the binarization of the image that means determine a single threshold. Obviously for images containing multiple objects such methods are not effective, it is necessary to separate the image into as many segments as many objects are in the picture, so *n* thresholds. Papamarkos N. and Gatos B. in "*A new approach for multithreshold selection*" (1994) are proposed a program that performs segmentation with multiple thresholds. Their method determines the histogram peaks (the maximum values), and finds the minimum between two maximums.

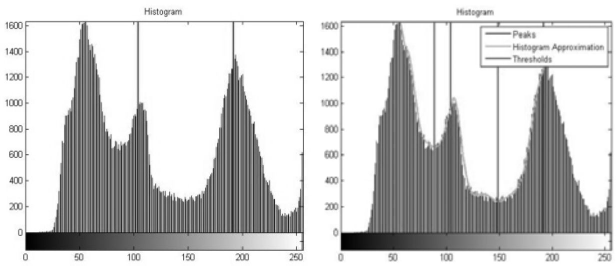


Figure 5. a) Maximums determination of the histogram (of image *butterfly* [20]); b) thresholds determination;

The irregular lighting influences the histogram: the peaks are not sharp and could not be separated by "valleys" they may look like in the figure below.

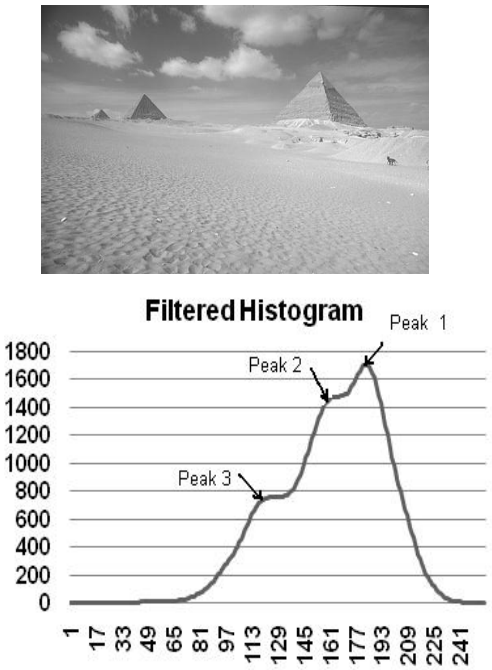


Figure 6. The test image #260058 [20] and the corresponding filtered histogram.

Notice in Figure 6 that histogram contains 3 Gaussians and the segmentation based on thresholds algorithm could detect only one (there peaks are not sharp and there are no "valleys"). In these cases it is recommended a Gaussian Mixture Model (GMM). This model is described in detail by Reynolds and Rose D.C. in "Robust Text-Independent Speaker Identification Using Gaussian Mixture Speaker Models". In the present work the authors refer to the model for acoustic signals. The model was taken over and implemented to the image segmentation, for example [22-23].

A Gaussian mixture model is a probability density function represented as a weighted sum of

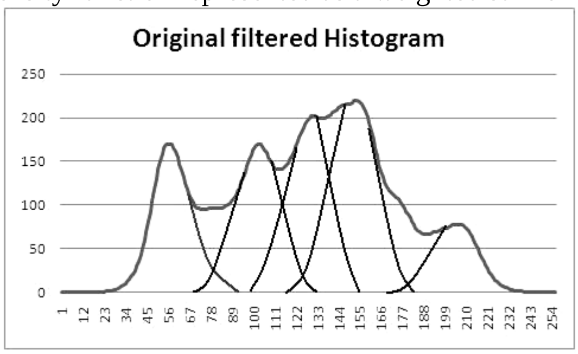


Figure 7. Gaussian Mixture Model (5 Gaussians)

$\boldsymbol{M}$ components with the Gaussian densities and can be written:

$$p(\boldsymbol{x} \mid \lambda) = \sum_{\boldsymbol{i}=1}^{\boldsymbol{M}} \boldsymbol{w_i}\, \boldsymbol{g}\left(\boldsymbol{x} \mid \mu_{\boldsymbol{i}}, \textstyle\sum_{\boldsymbol{i}},\right)$$

where $\boldsymbol{x}$ – represents a random vector with D dimension, $\boldsymbol{w_i}$ where i=1,...M – the mixture weights and $\boldsymbol{g}\left(\boldsymbol{x} \mid \mu_{\boldsymbol{i}}, \sum_{\boldsymbol{i}}.\right)$ – the components densities.

The components densities are the D- varied functions and can be expressed as:

$$\boldsymbol{g}\left(\boldsymbol{x} \mid \mu_{\boldsymbol{i}}, \textstyle\sum_{\boldsymbol{i}}.\right) = \frac{1}{(2\pi)^{\boldsymbol{D}/2} \mid \sum_{\boldsymbol{i}} \mid^{1/2}} \times$$
$$\times \exp\left\{-\frac{1}{2}(\boldsymbol{x}-\mu_{\boldsymbol{i}})' \textstyle\sum_{\boldsymbol{i}}^{-1} (\boldsymbol{x}-\mu_{\boldsymbol{i}})\right\} \qquad (2)$$

with the average of distribution $\mu_{\boldsymbol{i}}$ and covariance matrix $\sum_{\boldsymbol{i}}$. Mixtures weights must satisfy the condition $\sum_{\boldsymbol{i}=1}^{\boldsymbol{M}} \boldsymbol{w_i} = 1$.

A Gaussian mixture model is considered complete if it is characterized by the average distributions, covariance matrix and the weights of all components. This model can be expressed as a function of the parameters listed above:

$$\lambda = \{\boldsymbol{w_i}, \mu_{\boldsymbol{i}}, \textstyle\sum_{\boldsymbol{i}}\}, \qquad (3)$$

where $\boldsymbol{i} = 1,...,\boldsymbol{M}$.

GMM is poorly implemented in the image segmentation. Huang Z.K. and Chau K.W. [22] have developed an algorithm that can be applied only for bimodal histograms. Tang H. et al. [23]

believe that Gaussian mixture model based only on the distributions of intensity, is insufficient if the image is affected by noise. To solve this problem they propose a model that includes weight neighborhood (neighborhood weighted Gaussian mixture model). Experiments performed by the authors showed that their proposed method gets a better result in classification and is less affected by noise.

Completing the classical (basic) algorithms leads to better results.

A G-U-MM implementation is described in the article "Improved heterogeneous Gaussian and Uniform Mixed Models (G-U-MM) and Their use in Image Segmentation", authors Teodorescu H.N., Rusu M. sent to ROMJIST in May 2013. The flowchart of the developed algorithm is given below:

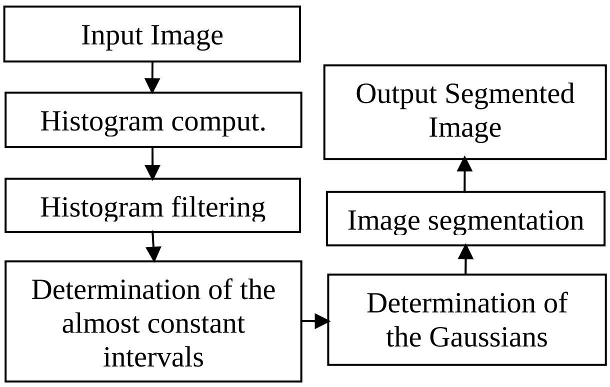


Figure 8. Flowchart of the proposed method used for image segmentation

The source code developed in C++ can be found at the address http://francophonie.utm.md/rusu_mariana/.

3. QUANTITATIVE QUALITY ASSESSMENT OF SEGMENTATION

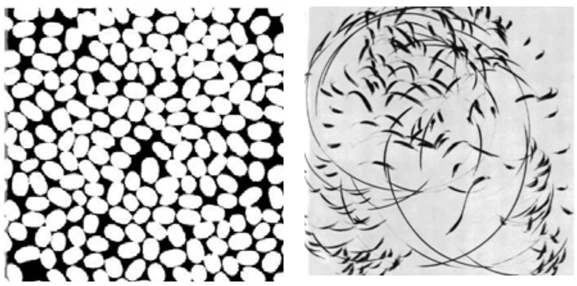
Evaluation of segmentation is done either manually by experts, or by using machine account. Supervised evaluation (involving human factor) is the delineation of regions by experts and comparing the results with obtained results and after algorithms implementation. http://www.eecs.berkeley.edu/Research/Projects/CS/vision/bsds/ site contains manually segmented images that can be used to assess the quality of segmentation.

This method is tedious and time consuming, so it tends to use quality assessment indices that would allow a non-supervised evaluation (without the involvement of experts).

In case of unsupervised evaluation is suggested more assessment metrics that would determine: the homogeneity of regions, the difference of averages between regions, the contrast between object and background, if too many or too few segments are obtained and others [24-26]. An important factor in quality assessing of segmentation is the evaluation of texture. Test images for this work do not contain textures, but the texture based segmentation is widely used in literature [27-28]. Sharma M., Markou M. and Singh S. analyse textural characteristics for precise regions determination [28]. An evaluation of the preliminary obtained results is described in the work "Quality Analysis of Image Segmentation based on G-UN-MMs", the authors Rusu M., Teodorescu H.N., presented at 2nd International Conference on Nanotechnologies and Biomedical Engineering, Chisinau, Republic of Moldova, April 2013.

A good segmentation evaluation method must be independent of the contents and types of image. It is necessary to determine most accurately the segmentation performance with minimal human involvement.

In order to make a comparison of the results using the proposed method with other methods from the literature, we primarily take into account the number of obtained segments. For each method the number of obtained segments should be the same for an objectively comparison.



a. b.

Figure 9. Original synthetic images *D75* (a) and *D45* (b) [20].

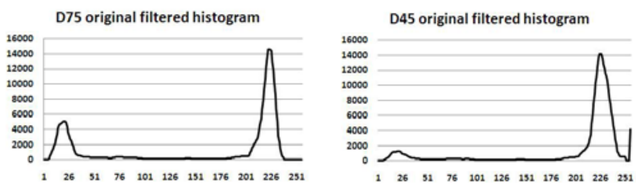


Figure 10. Original filtered histograms of synthetic images *D75* and *D45* [20].

We can observe that the histogram is composed of two Gaussians separated by one uniform distribution (3 segments). We need two thresholds.

The Multithresh (Papamarkos method) recommends other number of thresholds and we cannot make an objectively comparison between our (or Otsu) and this method because the number of obtained segments are different.

Table 1. Thresholds of synthetic images *D75*.jpg and *D45*.jpg

	*Thresholds of D75.jpg**
Multithresh	*0, 17, 73, 113, 153, 231, 255*
Otsu's method	*0, 25, 70, 255*
our method	*0, 54, 185, 255*
	*Thresholds of D45.jpg***
Multithresh	*0, 68, 81, 113, 152, 255*
Otsu's method	*0, 32, 76, 255*
our method	*0, 36, 185, 255*

* The recommended number of Thresholds is 6
** The recommended number of Thresholds is 5

In the literature are many quantitative objective evaluation methods [24-26], including:

- F, proposed by Liu and Yang;
- F′ and Q, proposed by Borsotti, Campadelli and Schettini;
- Intra-region uniformity criterion of Levine and Nazif;
- E – based on empirical analysis, proposed by Zhang et al.

The criteria we use are briefly presented below, paraphrasing the literature [24-26].

1) *Liu and Yang's evaluation function*:

$$F = \sqrt{N}\sum_{j=1}^{N}\frac{e_j^2}{\sqrt{S_j}} \tag{4}$$

where 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

$$e_j^2 = \sum_{k\in S_j}(x_k - \overline{x})^2 \tag{5}$$

where x_k is the gray level of the pixel, and the $\overline{x}$ means gray level of the region.

We can observe that F is biased towards small numbers of segments or large numbers of small segments. F tends to zero when is over segmentation (F is 0 when the color error is zero for all segments, it is only when each pixel form its own region).

2) *Borsotti, Campadelli and Schettini function* **F′** to improve upon Liu and Yang's method:

$$F' = \frac{1}{1000\cdot S_I}\sqrt{\sum_{a=1}^{MaxArea}[N(a)]^{1+1/a}}\sum_{j=1}^{N}\frac{e_j^2}{\sqrt{S_j}}$$

were S_I – image surface;
$N(a)$ – denote the number of regions in the segmented image having an area exactly the size *a;*
MaxArea – the area of the largest region in segmented image.

F' is better than F when the segmentation has lots of regions consisting of small number of pixels.

3) *Borsotti criterion*

$$Q = \frac{1}{10000\cdot S_I}\sqrt{N}\sum_{j=1}^{N}\left(\frac{e_j^2}{1+\log S_j} + \left(\frac{N(S_j)}{S_j}\right)^2\right) \tag{6}$$

were $N(S_j)$ – denote the number of regions in the segmented image having an area exactly S_j.

The segmentation with large numbers of regions is not penalized as heavily.

4) *Intra-region uniformity criterion of Levine and Nazif* [25]:

$$Lev = \sum_j\sum_{x\in R_j}\left(f(x) - \frac{1}{S_j}\sum_{x\in R_j}f(s)\right)^2 = \sum_j\frac{\sigma_j^2}{C} \tag{7}$$

$f(x)$ – the intensity of pixel x
C – normalized coefficient, equal to the maximum possible variance

$$C = \frac{(f_{\max} - f_{\min})^2}{2} \tag{8}$$

This criterion computes the sum of rapports between the normalized standard deviation of each region and the contrast of that region.

5) *Entropy-based evaluation method* [24]

As the authors say the entropy is a measure of the disorder within a region and is a natural characteristic to incorporate into a segmentation evaluation method.

The entropy for region *j* is defined as:

$$H_v(R_j) = -\frac{L_j(m)}{S_j}\log\frac{L_j(m)}{S_j} \tag{9}$$

where $L_j(m)/S_j$ represents the probability that a pixel in region R_j has a luminance value of m.

The notation $H_v(R_j)$ was simplified to

$H(R_j)$ with the default feature v being luminance. Zhang H. et al. define the expected region entropy of image I:

$$H_r(I) = \sum_{j=1}^{N} \left(\frac{S_j}{S_I} \right) H(R_j), \tag{10}$$

and the layout entropy:

$$H_l(I) = -\sum_{j=1}^{N} \left(\frac{S_j}{S_I} \right) \log \frac{S_j}{S_I}. \tag{11}$$

They propose to combine the both the layout entropy and the expected entropy measuring the effectiveness of a segmentation method:

$$E = H_l(I) + H_r(I). \tag{12}$$

For the natural images (standard test images), we determine the thresholds [see 29], that represent the limits of the Gaussian and uniform intervals, but we not obtained such good results as for synthetic images.

Table 2. Quantitative evaluation of the segmented image *butterfly* [20] using different methods.

The metrics	*Multithresh method*	*Otsu's method*	*Proposed method*
F	*333665*	*189539*	*278709*
F′	*0.0026*	*0.0015*	*0.0021*
Q	*0.0109*	*0.0040*	*0.0080*
Lev	*1.37*	*1.23*	*1.21*
E	*7.5*	*6.96*	*7.24*

For more details see [29]. Visually is difficult to assess which result of segmentation method is better, but the quantitative parameters show a difference.

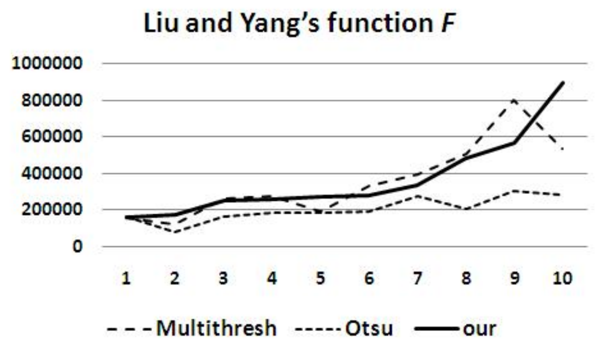


Figure 11. Representation of results using Liu and Yang's evaluation function.

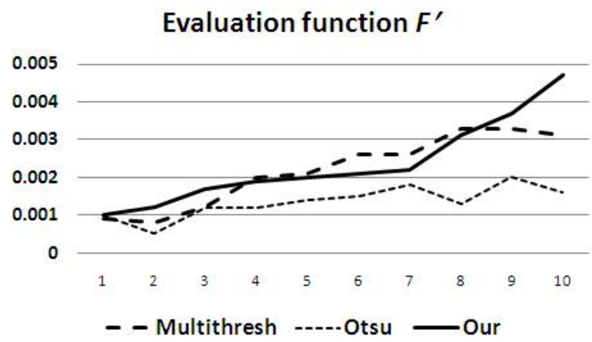


Figure 12. Representation of results using evaluation function F'.

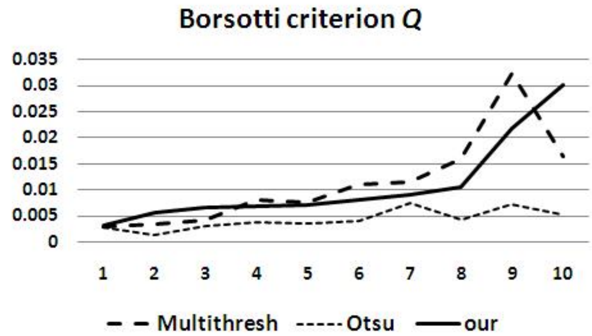


Figure 13. Representation of results using Borsotti criterion.

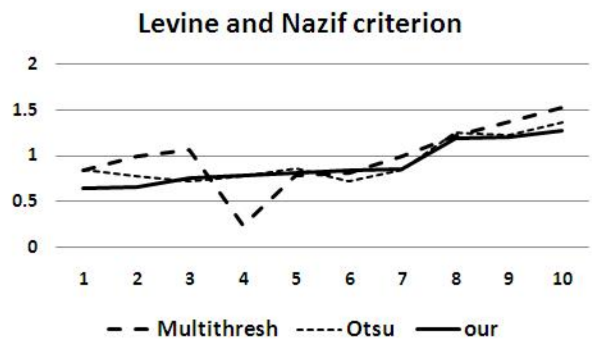


Figure 14. Representation of results using Levine and Nazif criterion.

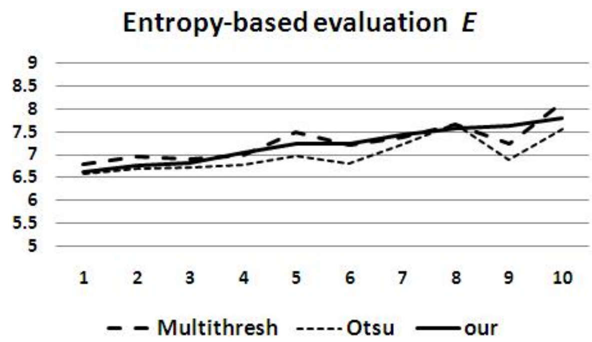


Figure 15. Representation of results using entropy-based evaluation method.

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 other more complex methods.

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 [18-19].

CONCLUSIONS

Segmentation is an essential step in image processing, of obtained results in this stage depends on interpretation quality of the scene by the computer (unsupervised method). Due to the many types of images (natural, SAR, medical) and the factors (irregular lighting, noise) that can influence the representation of objects in the scene was not yet developed an unique segmentation method that will produce satisfactory results for any type of image.

After preprocessing (filtering) we choose the segmentation method: pixel-based classification, edge based or regions based depending on the features required to extract: shapes, contours, regions, textures, text, etc. When choosing we consider the image type and the color spectrum. For example, the ultrasonic images are processed more complex methods using the wavelet. For the gray test images most effective (low complexity and fast computational) methods are based on pixel classification – thresholding and clustering; for the color images – regions based methods. Edge based methods are also widely used, because they are based on the determination of the color transition of values, which are effective for both cases.

Impulse noise (salt and pepper) influences greater the histogram based methods. All pixels with value 0 (black) are assigned of an area, and the pixels with the highest value (255 - white) on other areas. Another disadvantage of the histogram based methods is that the obtained segments are not adjacent homogeneous regions.

The edge based methods often get multiple or false contours. Because of irregular illumination (shadows, light spots) the edges of objects in the scene can be represented with dashed lines leading to erroneous interpretation of the scene.

Region-oriented segmentation methods are time consuming (each pixel in the image is compared to a randomly chosen pixel (germ) and check similarity to form homogeneous areas). It is more effective for color images.

The complexity of segmentation algorithm represents a compromise between the time spent on implementation and required accuracy of the results.

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