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An Adaptive Threshold-Gradient Method for Segmentation of Areas and Objects of Grey Scale Images

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1. Introduction

The segmentation of an image, i.e., the separation of the object from its background is one of the most important procedures in image processing.

Two basic types of segmentation exist at present – realized with respect to the intensity and to the intensity gradient, and two basic types of segments – areas and borders, respectively. The term "area" usually denotes toplogically joined regions of the image which have comparatively homogeneous distribution of intensity, while the term "border" relates to zones where the intensity changes sharply, or in other words, zones with greater value of the intensity gradient. Borders may be situated between an object and a background as well as between different regions of the object.

One of these two types of segmentation is usually applied for the purposes of image processing – the intensity or gradient (the latter being famous as segmentation by form), which, finally leads to partial use of the intensity characteristics of the picture. That is why a new adaptive threshold-gradient method is proposed in the paper. This method treats the image as one indivisible structure containing areas and borders. The analysis of this structure gives as a result the segmentation of the image.

2. Methods of intensity segmentation

The simplest method, called threshold method, consists in associating each element of the scene with one of the two groups - the group of the object or the group of the background depending on whether the intensity of the element exceeds a given threshold value or not [1, 2, 3]. The main problem in this method use is the correct choice of the threshold of separation. A widespread approach to the problem defines the selection of a threshold value, corresponding to the local minimum of the intensity histogram, which has to be bimodal. Unfortunately the histogram is generally unimodal, multimodal or step-like, and the threshold has to be defined by another method, for instance the entropy method, which analysis the entropy function of the intensity histogram, its maximum determining the optimum threshold of quantization [7, 8].

A method with varying thresholds has been describes in [10]. The image is sectioned in small rectangular regions, a histogram is formed for each one of them. In case it is bimodal, the threshold is calculated by its minimum, otherwise its value is obtained by interpolation of the thresholds from adjacent zones. The chief disadvantages of the threshold methods is the obtaining of false regions and the loss of regions aswell.

When using gradient methods of segmentation it is assumed that the shape of the object is fixed by its borders. The set of elements with sharply changing intensity is denoted as “borders” [11]. Different gradient operators for separation of borders are described in [7]: of Roberts, Sobel, Kirsh, Walsh, Laplace.

The main problem in the gradient methods is the appearance of false contours, their splitting and loss. Their advantage consists in the avoiding of the low-frequency noise in the image, i.e., the uneven illuminance. Human vision is sensitive to the contrast between the separate intensity areas and automatically ignores the irrgualar illuminance. The gradient methods take into account this feature of human vision and hence they are better than the threshold ones.

3. An adaptive threshold-gradient method for segmentation

3.1. Brief description of the method

In this method the connections between regions and borders in the image are described by the structural graph $\Gamma=(\boldsymbol{P},\boldsymbol{G})$, where $\boldsymbol{P}$ is the set of graph nodes, (the image areas), and $\boldsymbol{G}$ is the set of graph arcs (borders between the areas). Γ is an oriented non-plain graph, i.e., its arcs have direction and the graph configuration is spatial, not plain-like.

The image is considered a tridimensional surface $F(x, y, B) = 0$, from which the areas and objects are separated by a section with n tridimensional cutting surfaces $A_i(x, y, z)=0$, $i=1, 2, ..., n$.

The notions “potential” and “gradient” markers (PM and (GM) are introduced that are in fact points from the tridimensional space, which serve for the construction by approximation of the cutting surfaces. The latter can be regarded as adaptive threshold surfaces.

3.2. Definition of an optimal gradient threshold

The obtaining of a gradient vector $\vec{G}(x, y)$ in a point (x, y) is done by non-linear bidimensional discrete differentiation using Kirsh operator:

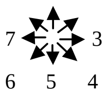
(1)

$a0$	$a1$	$a2$
$a7$	xy	$a3$
$a6$	$a5$	$a4$

$\vec{G}(x, y) = \max\{1, \max[5S_k - 3T_k]\}$,
where $k = 0, ..., 7$;
$S_k = a_k + a_{k+1} + a_{k+2}$;
$T_k = a_{k+3} + a_{k+4} + a_{k+5} + a_{k+6} + a_{k+7}$,

calculating the indices k by a module of 8.

The direction of the vector $\vec{G}(x, y)$ is indexed according to the scheme given below:



If the direction of $\vec{G}(x, y)$ is denoted by $DG(x, y)$, then $DG(x, y) = k$, and k is the index, for which the module of the gradient $\vec{G}(x, y)$ has a maximum value in conformance with (1).

All the areas, which are assumed as "gradient", i.e., where Θ_G is the differential threshold, must be separated from the gradient field, i.e., $|\vec{G}(x, y)| \geq \Theta_G$, at that Θ_G is a differential threshold and serves to separate the low contrasting intensity transitions and the homogeneous areas of high contrasting intensity transitions. An heuristic approach is proposed for the automatic determination of Θ_G, based on the analysis of the smoothed histogram $h_l(|\vec{G}|)$ of the gradient $|\vec{G}|$, obtained from the histogram $h(|\vec{G}|)$ according to the formula:

$$h(i) = (h(i-1) + h(i) + h(i+1))/3, \; i = 1, 2, \ldots, |\vec{G}|_{max}.$$

Θ_G is selected in such a way that the first derivative h_l' of h_l has maximal value in the point Θ_G.

The image is divided in two zones on the basis of the threshold Θ_G:

a) Gradient zone: the set $\boldsymbol{G}$ of pixels pix(x, y) for which $|\vec{G}(x, y)| \geq \Theta_G$,

b) Potential zone : the set P of pixels pix(x, y) for which $|\vec{G}(x, y)| < \Theta_G$.

An example division into zones for an one-dimensional case is shown in Fig. 1 along the axis x, where b denotes the function of pixels intensity. The notion "potential" zone is intuitively conceived after replacement of the intensity b by the third dimension z (height), i.e., the scene is considered as a tridimensioanal surface $F(x, y, z) = 0$.

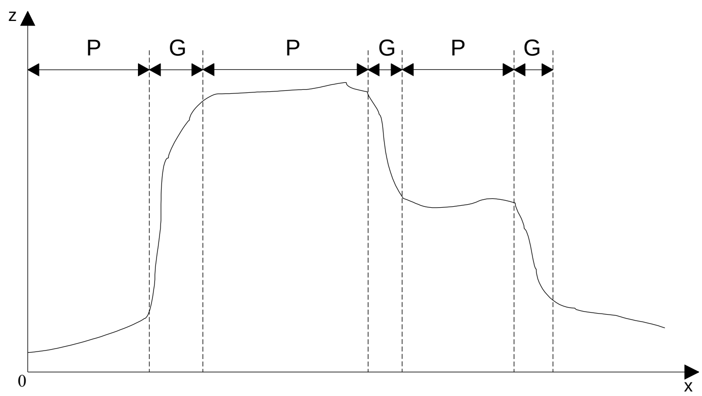


Fig.1

3.3. A concept for adaptive segmentation of an image using sectioning of its surface $F(x, y, z) = 0$ by an adaptive cutting surface $A(x, y, z) = 0$

The existing adaptive methods for threshold segmentation focus almost exclusively on a local area $m \times n$ and the adaptive threshold Θ_G is calculated for this area.

In the method described an adaptive surface $A(x, y, z) = 0$ is built approximating apriori selected points (Fig. 2), the selection being done not by the investigation of local areas of the image, that very often causes errors, but analyzing the complete gradient-potential structure of the scene, which gives an entire idea about the character of the connections between the potential areas P_l and the gradients G_j. Each area P_l, i=1, 2, ..., N_i and G_j, j=1, 2, ..., N_G, is an element of the sets $\boldsymbol{P}$ and $\boldsymbol{G}$ respectively, $P_l \in \boldsymbol{P}$, and $G_j \in \boldsymbol{G}$, where N_i and N_G denote the number of the potential and gradient fields in the image. The sets $\boldsymbol{P}$ and $\boldsymbol{G}$ are sets, obtained from $\boldsymbol{P'}$ and $\boldsymbol{G'}$ with the help of the surrection operation

The physical interpretation of this surrection transformation of the sets P_l' and G_j' into P_l and G_j respectively is the replacement of the intensities (gradients) of the corresponding pixels – elements of P_l' and G_j' by their averaged values for some small local areas $l \times l$. Then the sets P_l and G_j comprise these average values, the last being named potential and gradient markers:

$P_l = \{p_1, p_2, \ldots, p_{ni}\}$, $p_1, p_2, \ldots, p_{ni}$ – potential markers (PM);

$G_j = \{g_1, g_2, \ldots, g_{ni}\}$, $g_1, g_2, \ldots, g_{ni}$ – gradient markers (GM),

where ni is the number of PM for the i-th potential area, nj is the number of GM for the j-th gradient area.

The selection of the local areas $l \times l$ in order to get the average values, depends on the character of the image, i.e., whether it consists of smaller or larger details, which has to be known apriori. For the examples from Fig. 12 and Fig. 13, l=3 is chosen.

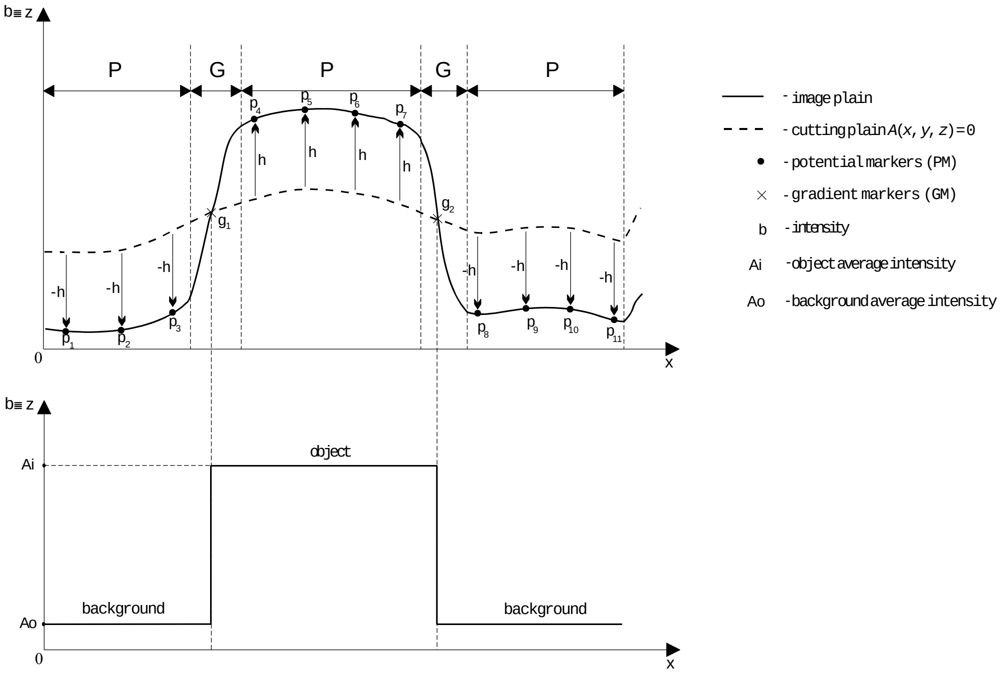


Fig. 2.

Fig. 3 shows an example, in which the cutting plain $A(x, y, z)=0$ is constructed in such a way that it passes across the gradient markers $g \in (G_1 \cup G_2)$ and is at a distance $+h$ from the potential markers (PM) $p \in P_2$ and at a distance $-h$ from the PM $p \in (P_1 \cup P_3)$.

The oriented non-plain graph $\Gamma=(\boldsymbol{P},\boldsymbol{G})$ is with nodes P_i and arcs G_j, the orientation of the arcs being assumed conditionally from black towards white level (down-up) – Fig. 4.

The average potential P_i (node Pi respectively) is computed for every potential area B_i:

$$B_i = \left(\sum_{k=1}^{n} b_k\right)/n, \tag{2}$$

where n is the number of pixels in the area P_i and b_k is the intensity (potential) of each one of them.

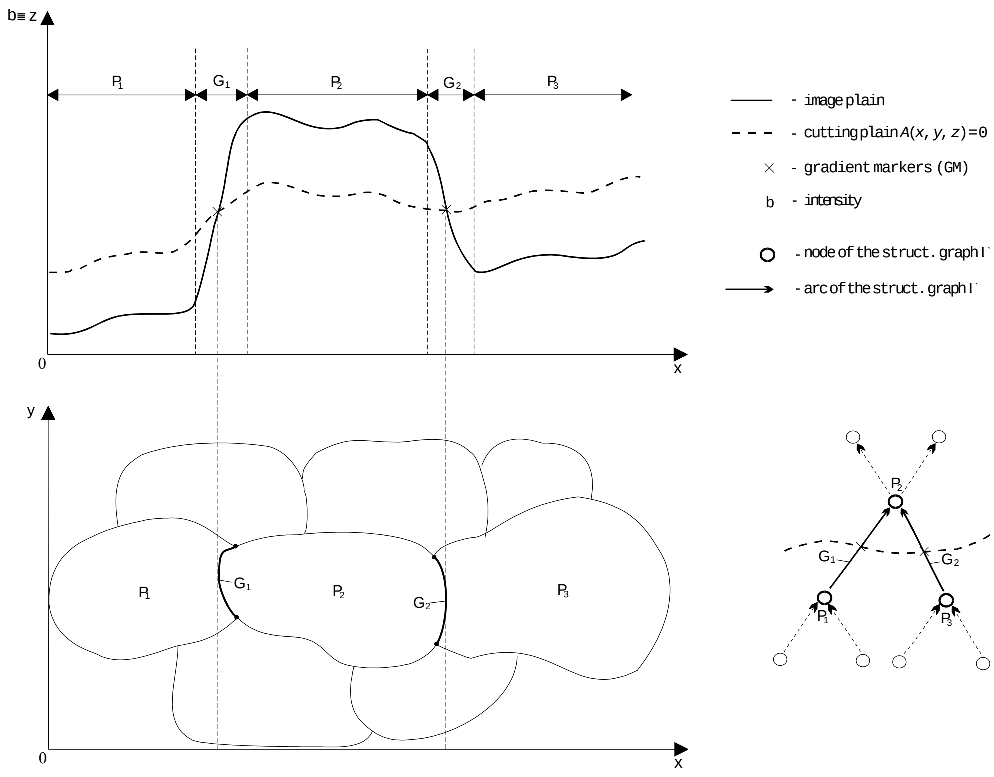


Fig. 3

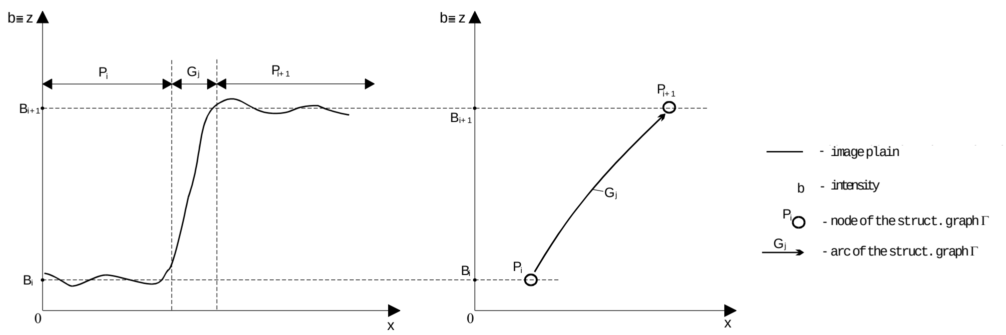


Fig. 4

3.4. Selection of the gradient (GM) and potential (PM) markers

3.4.1. Selection of PM.

The selection of a PM for a potential area P_i is done separating the area P_i by a grid $m \times n$. For example if $m=3$, the potential (average intensity) bp_k of the potential marker $p_k \in P_i$ is computed as the mean arithmetic of the intensities of the neighbouring pixels:

(3) $$bp_k = \left(\sum_{t=1}^{9} b_t\right) / 9,$$

The average potential B_i of the region P_i according to (2), is:

$$B_i = \left(\sum_{k=1}^{N_i} b\, p_k\right) / N_i , \tag{4}$$

where N_i is the number of PM in the area P_i.

3.4.2. Selection of gradient markers (GM)

The selection of gradient markers is realized defining the points with maximal slope of the intensity transition from the gradient areas G_j according to the following algorithm:

Step 1. The image is scanned by rows, until a pixel pix$(x, y) \in G_j$, $j=1, 2, \ldots, N_G$ is detected.

Step 2. A procedure for tracing a route with direction $\vec{g}$ is started, where $\vec{g}$ is a vector perpendicular to the intensity transition.

Step 3. The tracing of the route from the initial pixel pix(x, y) is realized, continuing in one of the eight possible directions $d=0, 1, \ldots, 7$ (0 being North, 1 – North-East, 2 – East, 3 – South-East, 4 – South, 5 – South-West, 6 – West, 7 – North-West). If d_n denotes the direction of $\vec{g}$ in the pixel pix(x, y) (which is initial or next point in the route), and d_b – the direction searched for, in which the tracing has to continue, then d_b is found according to the rule:

$$d_b = \begin{cases} (d_a-1)_{\mathrm{mod}8}, \text{if } |\vec{g}_{a-1}| = \max(|\vec{g}_{a-1}|, |\vec{g}_a|, |\vec{g}_{a+1}|) \\ d_a, \text{if } |\vec{g}_a| = \max(|\vec{g}_{a-1}|, |\vec{g}_a|, |\vec{g}_{a+1}|) \\ (d_a+1)_{\mathrm{mod}8}, \text{if } |\vec{g}_{av+1}| = \max(|\vec{g}_{a-1}|, |\vec{g}_a|, |\vec{g}_{a+1}|) \end{cases}$$

where $|\vec{g}_{a-1}|$, $|\vec{g}_a|$, $|\vec{g}_{a+1}|$ denote the gradients in three from the eight neighbouring to pix(x, y) points, which are reached, starting from pix(x, y) into one the three directions $(d_a-1)_{\mathrm{mod}8}$, d_a, $(d_a+1)_{\mathrm{mod}8}$ respectively.

Step 4. The route tracing is terminated in case the condition: $(\mathrm{pix}_{a-1} \in P_k) \cup (\mathrm{pix}_a \in P_m) \cup (\mathrm{pix}_{a+1} \in P_r)$ is satisfied, where P_k, P_m, P_r are potential areas and pix_{a-1}, pix_a, pix_{a+1} are the pixels being reached if started from pix(x, y) into one of the three directions $(d_a-1)_{\mathrm{mod}8}$, d_a, $(d_a+1)_{\mathrm{mod}8}$ respectively.

Step 5. The point with $\max|\vec{g}|$ must be selected among all the points belonging to the route traced, and it is the gradient marker.

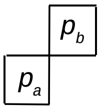
Step 6. The process goes to step 1 if not all the elements of the scene have been examined.

The advantage of the procedure above described is in finding of "representative" points from the gradient areas G (the so called gradient markers – GM), in which the slope of the intensity transition is maximal, since it is most correct that the border between the potential areas must past across the points with maximal value of the intensity transition gradient.

3.5. Building of the graph $\Gamma=(\boldsymbol{P}, \boldsymbol{G})$

In order to determine the areas $P_i \in \boldsymbol{P}$, $G_j \in \boldsymbol{G}$, it is necessary to apply for the potential and gradient markers twofold the procedure, described in [8], but with the following differences:

1. The connection type 8 is modified for the potential markers (PM) as follows:



If $|bp_a - bp_b| < \Theta$, then p_a and p_b are connected;

If $|bp_a - bp_b| \geq \Theta$, then p_a and p_b are not connected.

The purpose of this modification is to set apart the areas, that have splitted contours (weakly connected areas) as a border between them, as the regions P_1 and P_2 from Fig. 5. The hypothesis considered true, is that for the locations of slashing the inequality $|bp_a - bp_b| \geq \Theta$ is satisfied and hence the areas P_1 and P_2 are treated as separated. The threshold Θ is chosen lower that the threshold Θ_G. For example the choice for the image in Fig. 11 is Θ_G=14, Θ=8.

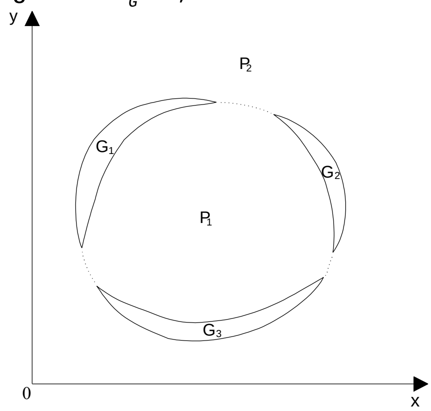


Fig. 5

2. The adjacent gradient markers g_a and g_b are not connected if:

a) $(d_a - d_b)_{mod8} > 1$, where d_a and d_b are directions of the gradient in points g_a and g_b.

b) If $L_a - L_b > \Theta_L$, where the threshold Θ_L is:

$$\Theta_L = K((L2_a - L1_a) + (L2_a - L1_a))/2,$$

i.e., the averaged levels of neighbouring transitions differ by any value greater than the threshold Θ_L, defined by the coefficient K. For the examples in Fig. 10 and Fig. 11 $K = 0,3$ is experimentally chosen

$L2_a$ and $L1_a$ are the intensity levels of the upper and lower end of the gradient transition passing through point g_a, and L_a is the intensity level in the point of the gradient marker g_a (Fig. 6).

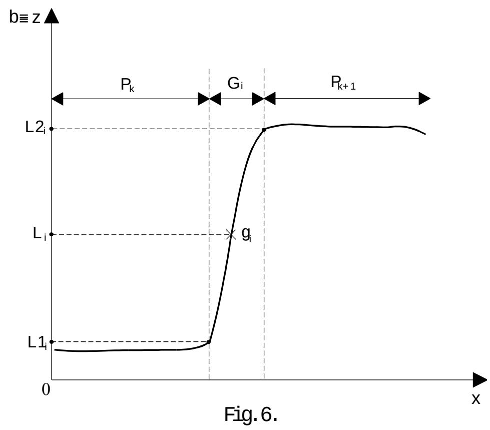


Fig. 6.

Condition 2a) means that transitions (the gradient areas) G_a and G_b have to be separated. They are topologically adjacent, but their directions do not coincide (Fig. 7). The meaning of condition 2b is the detection of transitions which are toplogically adjacent, but at different levels, i.e., they do not differ along axis z (Fig. 8).

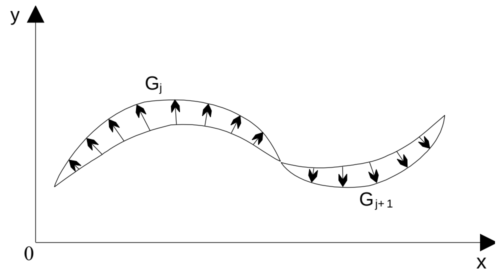


Fig. 7.

After the areas P_i and G_j, i=1, 2, ..., N_p, j=1, 2, ..., N_G, have been obtained, an oriented nonplanar graph $\Gamma=(\boldsymbol{P},\boldsymbol{G})$, has to be constructed, where $\boldsymbol{P} = (P_1, P_2, ..., P_{Np})$ is the set of the potential areas (PA) and $\boldsymbol{G} = (G_1, G_2, ..., G_{NG})$ is the set of gradient areas (GA).

The main rule to be observed in the formation of the graph Γ is that its arcs have to be oriented down to up, i.e., from black to white level, if it is assumed that the black level is down. Fig. 9 demonstrates an example of graph building.

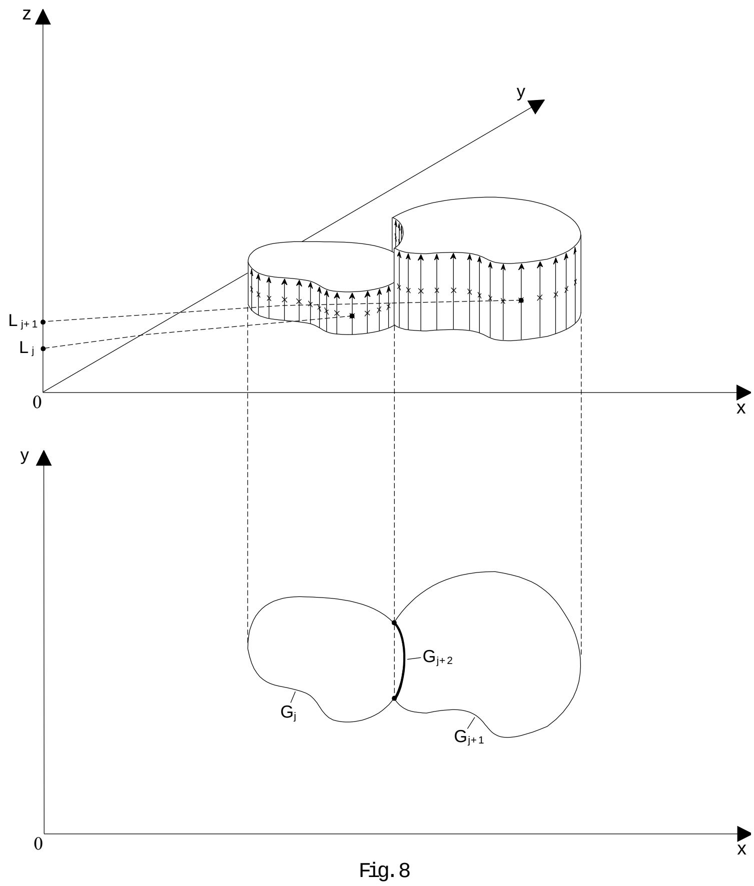
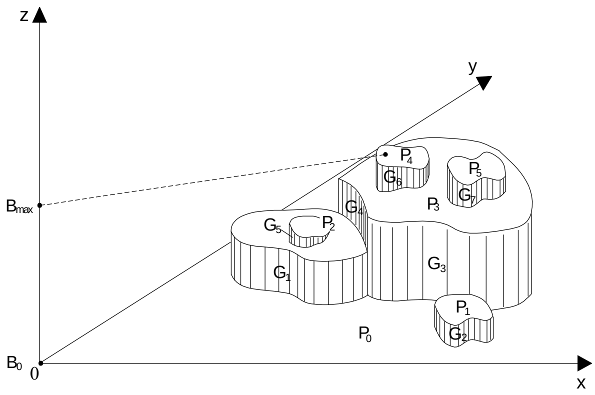


Fig. 8



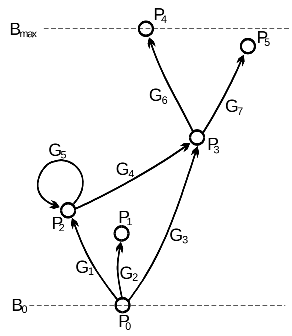


Fig. 9

3.6. A procedure for sectioning surfaces construction

In order to build the surface $A_i(x, y, z)=0$, it is necessary to know the initial approximation $A_i(x, y, z)=0$ and the points, through which the plain will pass, i.e., a problem for approximation of the surface with respect to given points is formulated.

3.6.1. Determination of the initial approximation

a) The plains $A_i(x, y)=C_i$, where C_i= const, are accepted as initial approximations, i.e., these plains are parallel to the plain (x, y).

b) The values C_i, i=1, 2, .., n, and the number n of the sectioning surfaces are determined by the modified intensity histogram $h(b)$, which is obtained from histogram $h(b_p)$, but on its hand it is a histogram of the intensities of the points pix(x, y), belonging to the set $\boldsymbol{P'}$: pix`$(x,y)\in\boldsymbol{P'}$. On the other hand $h(B)$ has still better expressed extremums, since $h(B)$ is obtained from $h(b_p)$ replacing the intensities b_p of PM, $p\in P_i$, by the average intensities B_i of the areas P_i. As a result the intensity-gradient regions P_i are equalized, and this equalization intensifies the differences between the extremums of $h(B)$, which on its turn is favourable for the process of determining the borders between the areas.

The coefficients C_i are defined to be equal to those values of B, for which $h(B)$ has a minimum.

In case the number of the maximums of $h(B)$ is equal to n+1, the number of the cutting surfaces is n.

3.6.2. Determination of the approximation points

A structured graph Γ=($\boldsymbol{P}$, $\boldsymbol{G}$) is applied for the purpose, using the so called iterative algorithm with dominating areas. This means that a sectioning surface is built at each iteration step, which has to separate (segment) the areas that are the brightest in a certain local region, i.e. “dominating”. The procedure determining the final successor (or node) in graph Γ is used.

The iterative procedure with n steps can be described by its i-th step as follows:

If for the i-th step as initial is assumed the graph $\Gamma^{i-1}=(\boldsymbol{P}^{i-1},\boldsymbol{G}^{i-1})$ from the (i–1)-st step, it serves for the construction of the subgraph $\Gamma^i=(\boldsymbol{P}^i,\boldsymbol{G}^i)$, which is a subset of Γ^{i-1}:$\Gamma^i\subset\Gamma^{i-1}$ and $\boldsymbol{P}^i\subset\boldsymbol{P}^{i-1}$ and $\boldsymbol{G}^i\subset\boldsymbol{G}^{i-1}$ respectively. The initial (the first) graph Γ is then denoted by the index^0, i.e., $\Gamma^0=(\boldsymbol{P}^0,\boldsymbol{G}^0)$,, where $\boldsymbol{P}^0\equiv\boldsymbol{P}$ and $\boldsymbol{G}^0\equiv\boldsymbol{G}$ are the complete sets of the potential and gradient areas correspondingly.

In order to make clear the process of graph Γ^i construction as a subset (subgraph) of the graph Γ^{i-1}, it is enough to explain the way of obtaining $\boldsymbol{P}^i$ and $\boldsymbol{G}^i$.

a) The subset $\boldsymbol{P}^i$ of $\boldsymbol{P}^{i-1}$ ($\boldsymbol{P}^i \subset \boldsymbol{P}^{i-1}$) is obtained as a difference: $\boldsymbol{P}^i = \boldsymbol{P}^{i-1} - \boldsymbol{P}^{i-1}_b$, where $\boldsymbol{P}^{i-1}_b$ is obtained as a subset of $\boldsymbol{P}^{i-1}_a$ and on its hand $\boldsymbol{P}^{i-1}_a$ is a subset of potential areas with average intensities B_j, for which $B_j > C_i$. This inequality means that the areas of average intensities B_j, located above the plain $\boldsymbol{A}_i(x, y) = C_i$ are "dominating". On the other hand the obtaining of $\boldsymbol{P}^{i-1}_b$ from $\boldsymbol{P}^{i-1}_a$ ($\boldsymbol{P}^{i-1}_b \subset \boldsymbol{P}^{i-1}_a$) is realized by the following procedure.

Procedure finding the final successors (nodes) of the graph $\Gamma^i = (\boldsymbol{P}^i, \boldsymbol{G}^i)$

The problem solved with the help of this procedure can be formulated as:

To obtain the subset $\boldsymbol{P}^{i-1}_b$ of those nodes that have incoming arcs only and none outgoing, from the subset $\boldsymbol{P}^{i-1}_b$ of the node of the grapg Γ^{i-1} for which $B_j > C_i$.

Two methods are proposed:

First method. The final successors must be detected for all possible oriented elementary routes passing through nodes from the set $\boldsymbol{P}^{i-1}_a$, and they will form the subset $\boldsymbol{P}^{i-1}_b$. According to [13] the notion "oriented elementary route" means a route in the graph, each of nodes and arcs in it being used more than once.

Second method. The rows, all the elements of which are zeroes, are separated from the matrix of he oriented graph. The nodes corresponding to the rows thus separated are the searched elements of $\boldsymbol{P}^{i-1}_b$.

Special attention has to be paid to the special case (Fig. 9), when cycles are obtained, i.e., one and the same arc is simultaneously going in and out of a given node. In this case the node P_2 is considered again as a final node, but the potential markers belonging to P_2 are not taken into consideration in the construction of this sectioning surface. The broken contour G_5 is closed by the intersection of the cutting surface $A(x, y, z)$ and the surface of the image $F(x, y, z)=0$.

b) The subset of the arcs $\boldsymbol{G}^{i-1}_b$ is obtained from $\boldsymbol{P}^{i-1}_b$ as a subset of arcs, entering the nodes belonging to $\boldsymbol{P}^{i-1}_b$. After that in an analogous way to a), $\boldsymbol{G}^i = \boldsymbol{G}^{i-1} - \boldsymbol{G}^{i-1}_b$ is defined.

Having the subsets $\boldsymbol{P}^i$ and $\boldsymbol{G}^i$ for the i-th surface $A_i(x, y, z)=0$, the points that approximate A_i are determined as follows:

1. The gradient markers g_{i1}, crossed by the surface A_i are elements of the set $\boldsymbol{G}^{i1}_b$, which is an element of the set $\boldsymbol{G}^{i-1}_b$.

$$\boldsymbol{G}^{i-1}_b = \{G^{i1}_b, G^{i2}_b, \ldots, G^{iR}_b\},$$

$$G^{il}_b = (g_{il1}, g_{il2}, \ldots, g_{ilQ}) \text{ for } L = 1, 2, \ldots, R,$$

where R is the number of the gradient areas G^{il}_b, belonging to the subset $\boldsymbol{G}^{il}_b$ and Q is the number of the gradient markres g_{i1} belonging to G^{il}_b.

2. The potential makers p_{il}, that are at a distance $+h$ from the surface A_i, are elements of the set P^{il}_2, which on its turn is an element of the set $\boldsymbol{P}^{i-1}_b$:

$$\boldsymbol{P}^{i-1}_b = \{P^{i1}_b, P^{i2}_b, \ldots, P^{iK}_b\},$$

$$P^{il}_b = (p_{il1}, p_{il2}, \ldots, p_{ilT}) \text{ for } l = 1, 2, \ldots, K,$$

where K is the number of potential areas P^{il}_2, belonging to the subset $\boldsymbol{P}^{i-1}_b$, and T is the number of the potential markers p_{il} belonging to P^i_b.

3. The potential markers, located at a distance $-h$ from the surface A_i, are elements of the set P^{il}_b, which is an element of the set $\boldsymbol{P}^i_b$.

$$\boldsymbol{P}^i_b = \{P^{i1}_b, P^{i2}_b, \ldots, P^{iM}_b\},$$

$$P^{il}_b = (p_{il1}, p_{il2}, \ldots, p_{ilS}) \text{ for } l = 1, 2, \ldots, M,$$

where M is the number of potential areas P^{il}_b, belonging to the subset $\boldsymbol{P}^i_b$, and S is the number of the potential markers p_{il} belonging to P^{il}_b.

The distance h, called distance of separation, is experimentally defined. For Figs. 10 and 11, h is assigned Θ_G.

After the initial approximation and approximation points have been determined, a second iteration algorithm (4-steps) is applied to build a "smooth" sectioning surface A_i. This iteration algorithm consists in successive application of the operation program-recursive filtration on the surface of initial approximation $A_i(x, y) = C_i$ and the marker points (PM and GM) for the four different directions.

3.6.3. An algorithm for program-recursive filtration

Step 1. For the points fixed a_i, it is assumed $z_i = a_i$, where a_i is the value of the corresponding marker (PM or GM).

Step 2. The following operation is applied for all the points outside a_i:

$$b = \left(\sum_{j=1}^{9} b\, x_j \right) / 9 .$$

The segmentation implemented on the image $F(x, y, z) = 0$ by n sections with the help of the cutting surfaces $A_i(x, y, z) = 0$, $i = 1, 2, ..., n$, can be regarded as a local threshold operation, applied n times for each pint of the picture pix(x, y):

If $b(x, y) \geq z_i(x, y)$, then pix(x, y) $\in O_i$,

If $b(x, y) < z_i(x, y)$, then pix(x, y) $\in \Phi_i$,

where z_i is a point from the A_i-th surface, and O_i and Φ_i denote conditionally the object and the background for the i-th section.

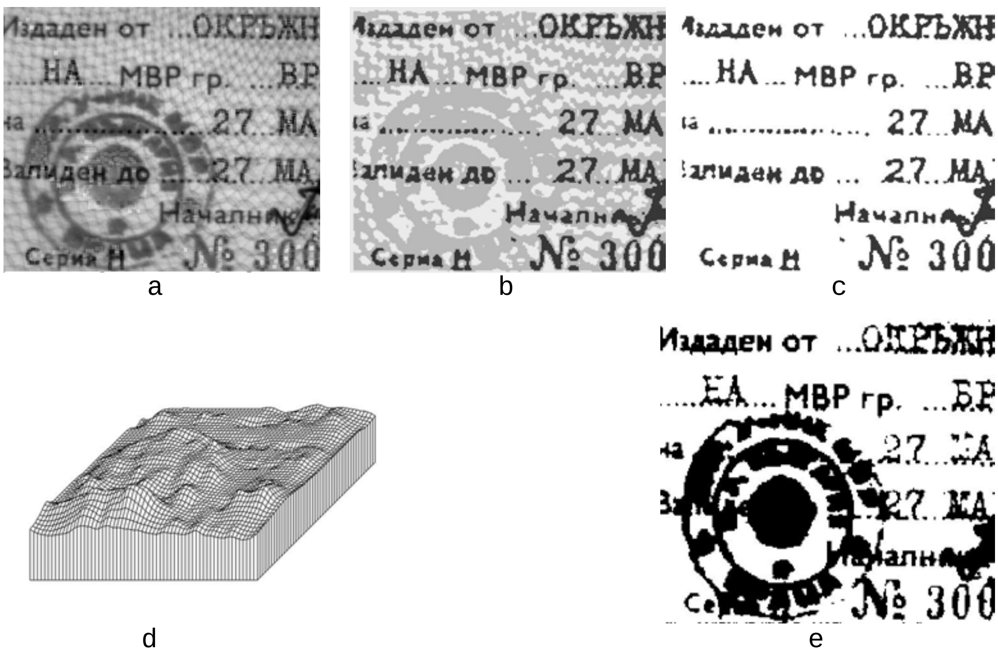


Fig. 10

4. Experimental results

Fig. 10 and Fig. 11 show two possible applications of the method. Fig. 10a and Fig. 11a show the initial images of printed documents (a passport and text) with uneven illuminance, unequal background–texture and bad quality. Fig. 10b and 11b show the images after segmentation in three levels (with two sectioning surfaces respectively), and Fig. 10c and 11c – the final results, i.e., segmentation in two levels – text and background, and Fig. 10d and Fig. 11e demonstrate the results from another method – a threshold one, optimizing the threshold according to an entropy method [8].

Fig. 10d, 11d and 11e show the cutting surfaces of the two scenes. A tendency is noticed that the sectioning surfaces "go round" the irregularities of the background, which helps the exact separation (without false areas and contours) of the images and the background.

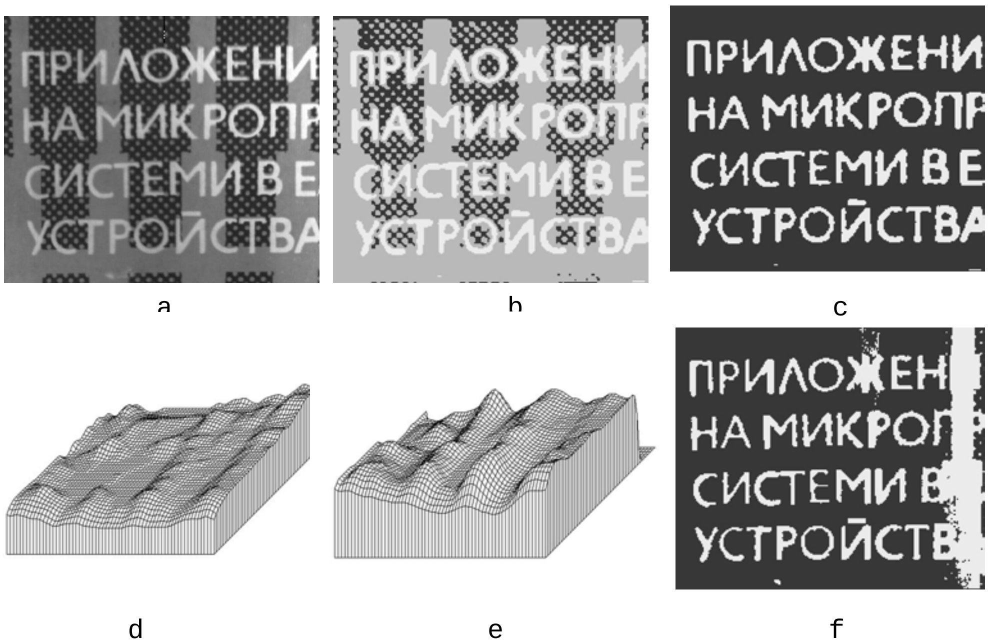


Fig. 11

5. Conclusion

The application of the method proposed is various – for analysis of tridimensional scenes with arbitrary location of the illuminating source, for coding of the image homogenizing areas, for analysis of printed documents wit irregular background and poor quality, for reducing the number of the intensity levels and removing the information redundancy, etc.

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Адаптивный порогово-градиентный метод для сегментирования областей и объектов в полутоновых изображениях

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Описывается новый адаптивный порогово-градиентный метод для яркостного сегментирования, при котором изображение рассматривается как совокупность границ и областей. Для их описания используется структурный граф.

Сегментирование осуществляется с помощью трехмерных поверхностей, рассекающие граф. Их число определяется в зависимости от минимумов модифицированной гистограммы яркостей. Введены понятия потенциальный маркер и градиентный маркер, которые используются для построения секущих поверхностей.

Метод можно применять как для обработки документов плохого качества, так и для кодирования изображений через гомогенные области.