

[16] Boundary extraction from images using clustering algorithm

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Abstract

The paper suggests an algorithm of boundary extraction based on image clustering. In the process of clustering, the image is decomposed into simply connected regions based on pixel color. Edges of the regions are considered as the boundaries. The proposed approach allows obtaining well defined boundaries without blurring. The algorithm is highly resistant to impulse noise.

Keywords: BOUNDARY EXTRACTION, EDGE DETECTION IN AN IMAGE.

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Introduction

Boundary extraction must be performed on digital images in the process of solving many problems related to the graphical objects analysis. Most of algorithms of boundary extraction are now based on differential operators. The basic idea of all these methods is that on boundary edges the two-dimensional color intensity function is discontinuous, which may be determined by examining derived functions of light intensity. Differential methods of boundary extraction consist of two stages. First, intensity fluctuations are amplified. Secondly, boundary points are extracted using threshold methods. It should be noted that differential methods increase impulse noise.

Most of methods of image boundary extraction are based on investigation of a color intensity gradient. One of the historically first methods was the method offered by L. Roberts [1], which was based on the use of a cross matrix operator containing finite differences of neighboring elements. Later, J. Prewitt proposed an operator based on the notion of the central difference [1]. The main disadvantage of this approach is noise sensitivity. The best known method of all differential methods of boundary extraction is based on the Sobel operator [1]. This approach is also based on central differences, but the weight of central elements has been doubled. The main disadvantage of the Sobel operator is the lack of a perfect rotational symmetry. Scharr attempted [1] to reduce negative effects of the Sobel operator by increasing the central element weight which succeeds the weight of edge pixels by 3.3 times. More sophisticated approaches are based on extraction of a certain function weighting the pix-

el, depending on its distance to the central pixel [2]. This method has additional ability to suppress noise. Another set of differential methods of boundary extraction is based on the use of the Laplacian operator [3], for calculation of which the derivatives of the second order must be differentiated. In paper [4] a two-stage algorithm was offered, in which before using the linear differential operators, the image was decomposed in the ring $Z/2^p$ followed by connecting the boundaries.

Statistical methods of boundary extraction, as well as wavelet transform methods are used as an alternative to differential filters. In paper [5] the rank detector method of boundary extraction is offered using special statistics to make a decision on whether the pixel belongs to the boundary. Paper [6] offers a modification of this method and a threshold extraction method is proposed herein.

In papers [7,8] the image region edge detection algorithms have been proposed using mathematical morphology methods. In paper [9] boundary extraction is performed on the basis of the concept of the digital half-tone image using the Markov process. Individual pixels are represented herein as the states, and the relationship between them – as the transition probability.

In paper [10] the method of boundary extraction based on a double wavelet transform is offered. The proposed method enables to adjust a level of details and has a higher accuracy compared with differential filters. In paper [11] a wavelet transform has been used to construct a sequence of images with different detailization levels and to extract structural elements of different scale.

In this paper we have proposed a new approach to extract boundaries based on hierarchical image clustering. This approach allows us to consistently extract boundaries of differing intensity. An important positive feature of the proposed method is its resistance to impulse noise that favourably distinguishes it from traditional differential filter.

I. Problem description and problem-solving procedure

We shall search the curve lines on the image which limit simply-connected regions of the same color. This problem shall be solved in two stages. At the first stage, we shall select simply-connected regions of the same color. At the second stage, we shall find the curve lines which limit these regions.

Let us assume the image as a set of points of the five-dimensional space RGBXY. The first three coordinates of each point are determined by a pixel color component; the last two coordinates are determined by pixel coordinates on the image. In order to avoid domination of one type of coordinates over the other, we shall normalize the coordinates. Suppose a palette contains g of color tones for each color and the image has a size of $M \times N$. Let us select a minimum spatial image size $L = \min(M, N)$ and scale a color range by multiplying all color values by the factor L/g .

Let us contrast the constructed set of points to a fully connected graph. The set of graph nodes will coincide with the set of image pixels. The edge length will be equal to the Euclidean distance between points in the five-dimensional space RGBXY. The distance between the points v_i and v_j will be denoted as $d(v_i, v_j)$. In order to extract simply-connected regions of the same color we shall cluster the constructed graph. For graph clustering we use the algorithm based on constructing a minimum spanning tree [12]. When using this algorithm with regard to the graph comparing the image, it is possible to construct a greedy algorithm with a relatively high operating speed. The greedy algorithm allows obtaining the minimum spanning tree without constructing the whole graph. This is important since data storage for the whole fully connected graph requires a large memory and a large processing time.

A step of the greedy algorithm can be described as follows. Suppose that at some certain stage a part of the tree T_k containing the nodes $\{v_{i1}, \dots, v_{ik}\}$ has been constructed. We consider the nearest neighbors of each of the nodes included in T_k . We extract such node, the distance from which to one of the nodes T_k is considered to be the minimum. We shall construct the part of the tree T_{k+1} connecting the extracted node v_{ik+1} to the tree T_k . We shall continue the algorithm until all nodes are used up. An important issue is to select a starting

point which will act as a tree root. Absolutely random selection of this point can provide multi-valued results. A point representing the single pixel cluster may be randomly selected. According to further experiments, we succeed in achieving the best results, if one of the points of the large cluster has been extracted as the root. Therefore, in the process of random selection of the root node, we shall demand that all eight of its closest neighbors in the image have the same color with a certain accuracy considering the nuances.

Clustering consists in decomposition of the minimum spanning tree into sub-trees. Decomposition is performed by discarding some edges. From the algorithm logic it follows that the existing cluster "nucleus" will first be connected to the pixels located along its boundary and similar in color. When these points have been used up, transition will be performed to one of the points which significantly differ in color. This transition corresponds to the transition to a new simply-connected region of the same color. Such transitions can be detected according to a dependency graph of edge lengths in accordance with their connection procedure. Transition moments will correspond to the nodes on the graph. Fig. 1 shows the graph examples for an artificial image with clear boundaries (Fig. 1a) and a photographic image with blurred boundaries (Fig. 1b).

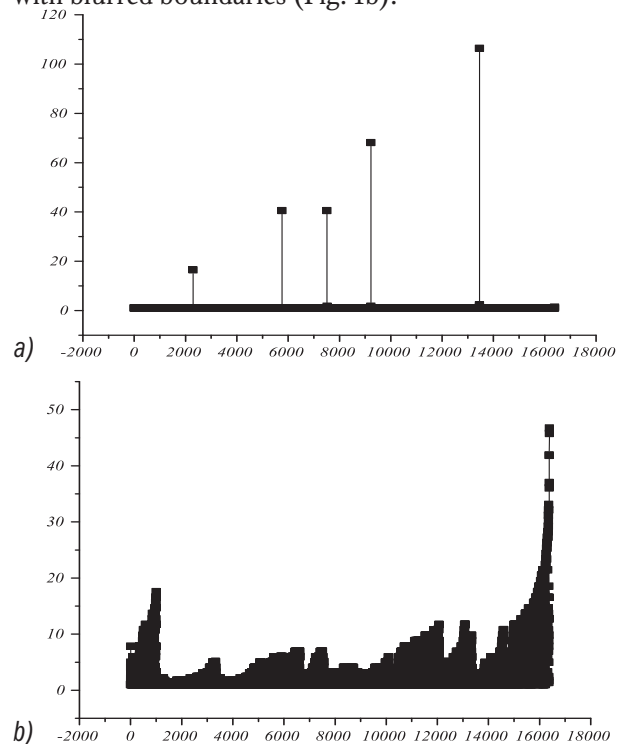


Fig. 1. Examples of dependency graphs of the edge length and a serial number of its appearance for different images: a) the artificial image with clear boundaries, b) the photographic image with blurred boundaries

As expected, node extraction and clustering is a fairly simple task for artificial images. It is much more complicated to extract nodes for photographic images. Therefore, we will be building a cluster hierarchy. We shall find the longest edge, which removal would separate the sub-tree consisting of more than one node. Let us denote its length by R_0 . We shall conduct the first-level clustering thus discarding the edges longer than $0.9R_0$. In the process of clustering of the second level, we shall discard edges longer than 0.9^2R_0 . Generally, in the process of k -level clustering, we shall discard the edges longer than 0.9^kR_0 . At each step before discarding the edge, we shall check whether it does not separate the cluster consisting of one node; so we won't delete such edges. Experience has proven that it would be sufficient to perform clustering for no deeper than the fifth level to extract main boundaries.

After clustering has been performed for each cluster, we shall denote its boundary with one pixel in thickness. This operation has a linear complexity since it requires single searching of pixels and checking a number of neighbors, included into this cluster, for each of them. The boundary constructed thereby will have a thickness of two pixels, so edge pixels shall be determined for each of the adjoining clusters.

2. Computer experiment

The experiment was conducted both in artificial images and in pictures of various objects. Drawings with clearly distinguished geometric figures were used as artificial images.

Fig. 2 shows the artificial image and the regions boundaries obtained thereto. It should be noted that for the artificial image we have only to perform clustering of the first level. As we can see, the regions boundaries are exactly defined and have two pixels in thickness. The line thickness is always equal to two, because the boundary is represented as an interface between two clusters. By the construction of the cluster's boundary it has a single thickness from each side.

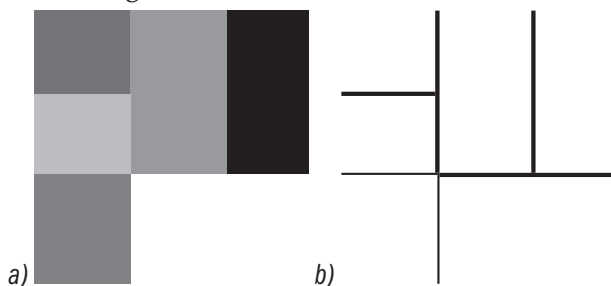


Fig. 2. Boundary extraction for the image with uniform filling: a) the original image, b) the regions boundaries extracted by the proposed algorithm

Fig. 3 shows a natural image with the clear boundary. As can be clearly seen, the proposed algorithm allows extracting the boundary with high accuracy.

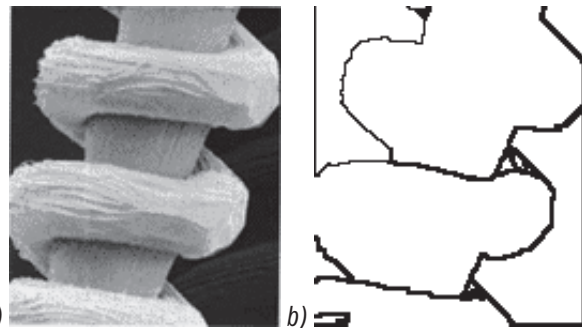


Fig. 3. Boundary extraction for the natural image with sharp boundaries: a) the original image, b) the regions boundaries extracted by the proposed algorithm

We shall apply the proposed algorithm to photographic images. Fig. 4 shows the results of the algorithm performance for the image "Peppers". As is clear from the figure, we have already succeeded on the fourth level in extracting all main image contours.



Fig. 4. Resulted algorithm performance for the image "Peppers": a) the original image, b) the contours resulting from the 4th level clustering

Let us perform the experiment with resistance of the proposed algorithm to random impulse noise. Results for the artificial image are shown in Fig. 5. As we can see, the presence of random impulse noise in solid color areas does not affect the results, i.e. a noise amplification effect typical for differential filters is missing in the proposed algorithm. The presence of noise can lead only to slight blurring of the boundary line. A detailed pixel-by-pixel image analysis has shown that blurring occurs at those points, where the pixels damaged by noise get either into the boundary or to its neighboring points, i.e. the boundary is blurred even in noisy images.

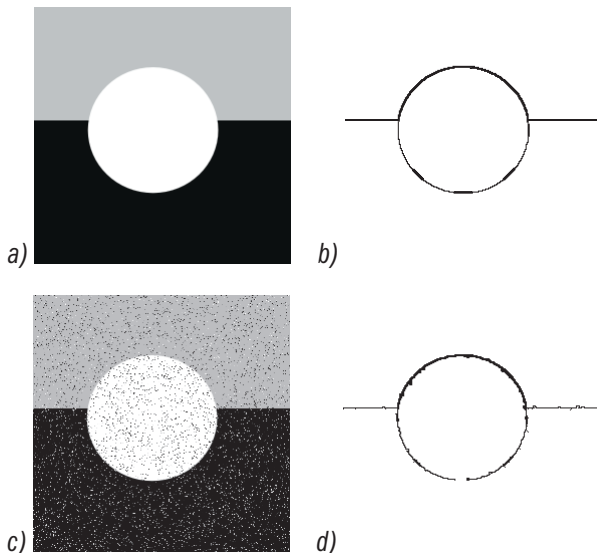


Fig. 5. Resistance of extracted boundary to random impulse noise with intensity of 10% for the artificial image: a) the original image, b) the boundaries extracted for the original image, c) the image noised by 10%, d) the boundaries extracted for the noisy image

Let us perform the similar experiment to test resistance of the proposed algorithm to random impulse noise for the image "Peppers." The results are given in Fig. 6.

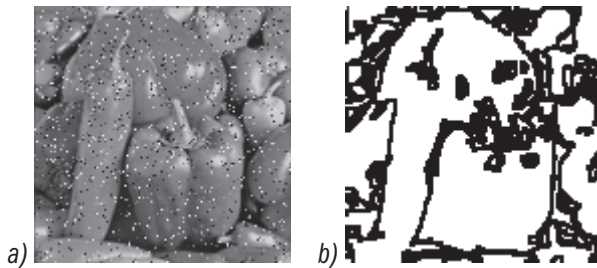


Fig. 6. Resistance of extracted boundary to random impulse noise with intensity of 10% for the image "Peppers": a) the image noised by 10%, b) the boundaries extracted for the noisy image

Comparing Fig. 6b with Fig. 4b shows that for photographic images the algorithm of boundary extraction is resistant to impulse noise in the same way as for artificial test images.

3. Discussion of results and conclusions

Let us compare the results obtained in this paper with the data obtained in similar works. In paper [13] the basic quality criteria of searching boundaries have been described in detail. In order to compare the algorithms we shall use in this paper the following criteria such as boundary sharpness, thickness of boundary lines, resistance to noise and arithmetic complexity of the algorithm. The proposed algorithm of boundary

extraction has many specific features compared with widely spread filter-based approaches. First, the approach based on clustering allows us to obtain clear boundaries. We use the term the boundary sharpness to mean a range width of intensity transition for the identified boundary from the minimum value to the maximum. I.e. the less the width of this range, the higher the sharpness of the boundary. Fig. 7 shows intensity graphs of the identified boundaries and the corresponding transition ranges, where the boundaries have been identified in different ways.

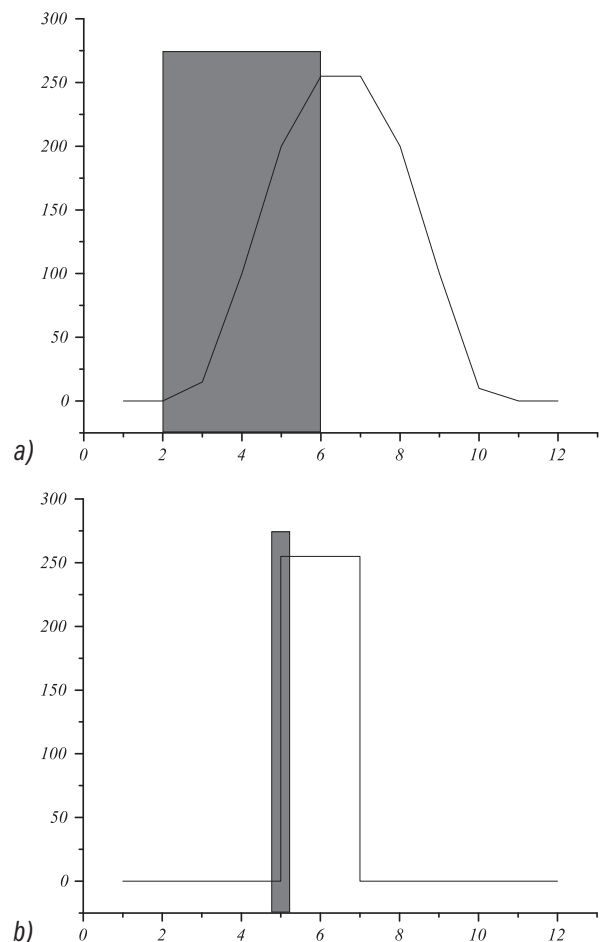


Fig. 7. Intensity graphs of the identified boundaries and the corresponding transition ranges (the ranges are gray-filled): a) the boundaries identified by the Sobel operator, b) the boundaries identified by the clustering method

The boundaries extracted by the method proposed hereby are represented by the lines with two pixels in thickness. If necessary, skeletonization algorithms [14, 15] may be applied to these lines and their thickness may be reduced to one pixel. Thus the problem of thickness of boundary lines may be solved. We have to

separately examine the blurred boundaries in applied differential filters constructing color intensity distributions, and to use additional post-processing techniques in order to reduce it [3]. The second problem which is solved better, when using the proposed approach than when using differential filters, is to reduce noise influence. As mentioned in the introduction, application of differential operators for the image with random impulse noise shall result in increased intensity of damaged pixels [4]. It is supposed to solve this problem either by image pre-processing with the help of smoothing filters which reduce noise intensity or by using additional transformations, e.g., the wavelet transforms. As the filter reducing noise intensity, we may use the rank filtering [16], however it can result in increased blurring of the boundary being obtained. In order to solve this problem we need to introduce an additional step, where the boundary sharpness is increased by their approximation using an exponential function [17]. The third advantage of the proposed method is the possibility to vary a detailization level of boundaries being extracted. Through selecting different levels of clustering, we can extract first the boundaries with the highest intensity difference, then with smaller intensity difference and so on. Thus, it is possible to solve the boundary extraction problem with a given level of accuracy. Fig. 8 shows two detailization levels of extracted boundaries for the image "Peppers".

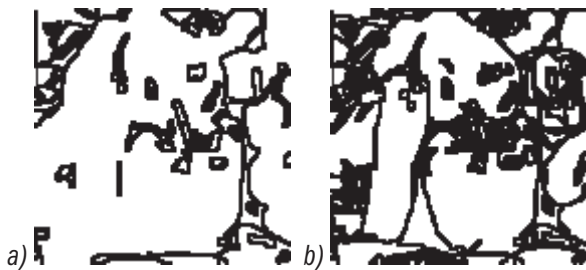


Fig. 8. Detailization levels of extracted boundaries for the image "Peppers": a) the boundaries obtained during the 3rd level clustering, b) the boundaries obtained during the 5th level clustering

Among disadvantages of the method proposed herein, we may note its greater complexity compared with differential filters. As you know, the filters possess the linear complexity ($O(n)$, where n – is a number of pixels in the image). The proposed algorithm is characterized by a quadratic complexity $O(n^2)$. However, this loss of runtime is not significant, since the algorithm remains polynomial that is considered to be acceptable for this type of problems. Besides, the offered algorithm is characterized by rich parallelization opportunities which improve its possible practical value.

The proposed algorithm can be used in user authentication problems in accordance with their image, since it allows rather accurately locate the main points (contours of a facial oval, eyes, a mouth, a nose), which use face recognition systems. Fig. 9 shows the result of processing of human face photography.

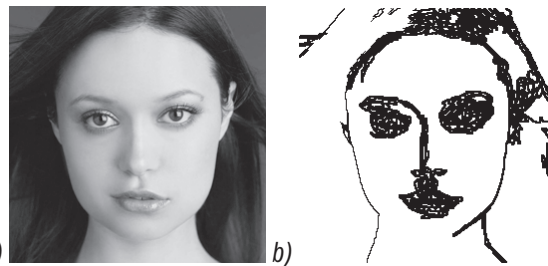


Fig. 9. The example of processing of human face photography: a) the original image, b) human facial contours

Resistance of the proposed method to impulse noise allows us to widely use it in computer vision systems transmitting signals over noisy channels.

References

- I. Fisenko, V.T.** Computer image processing and recognition / V.T. Fisenko, T.Ju. Fisenko. – Saint-Peterburg: "SPbGU ITMO" Publisher. – 2008. – P. 192. (In Russian).
- 2. Popov, G.A.** About one method of low-speed filtration of sonar images / G.A. Popov, D.A. Hrjashchjov // Astrakhan Technical State University Reporter: Marine Machinery and Technology Series. – 2010. – Vol. 1. – P. 63-68. (In Russian).
- 3.** Computer Image Processing, Part II: Methods and algorithms / A.V. Chernov, V.M. Chernov, M.A. Chicheva, V.A. Fursov, M.V. Gashnikov, N.I. Glumov, N.Yu. Ilyasova, A.G. Khramov, A.O. Korepanov, A.V. Kupriyanov, E.V. Myasnikov, V.V. Myasnikov, S.B. Popov, V.V. Sergeyev; ed. by V.A. Soifer. – VDM Verlag. – 2009. – P. 584.
- 4. Zharkih, A.A.** Two-stage algorithm of allocation of contours images / A.A. Zharkih // Moscow Technical State University Reporter. – 2009. – Vol. 12(2). – P. 202-205. (In Russian).
- 5. Grebenshnikov K.D.** Rank detector of local contour features of the image with a fixed level of artificial positives / K.D. Grebenshnikov, A.A. Spektor // "Avtometrija" Publisher. – 2001. – Vol. 4. – P. 119-127. (In Russian).
- 6. Bondina N.N.** Using of statistical characteristics to marking of borders in medical images / Krivencov V.Je. // National Technical University "HPI" Reporter. – 2013. – Vol. 39(1012). – P. 22-27. (In Russian).
- 7. Huang C.P.** An Integrated Edge Detection Method Using Mathematical Morphology / Wang R.Z. // Pattern Recognition and Image Analysis. – 2006. – Vol. 16(3). – P. 406-412.
- 8. Buj T.T.Ch.** Analysis of methods of digital images edge detection / Spicyn V.G. // Doklady TUSURa. – Vol. 2(22). – Chap. 2. – P. 221-223. (In Russian).

- **9. Kurbatova E.E.** Combined algorithm for contour detection in objects of interest in monitoring systems / Medvedeva E.V., Orlov I.Ja. // Lobachevsky State University Reporter. – 2013. – Vol. 2(1). – P. 60-65. (In Russian).
- **10. Antoshhuk, S.G.** The edge selection of object images by double hyperbolic wavelet transform method / S.G. Antoshhuk, O.Ju. Babilunga, A.A. Nikolenko // Electrical Machine-building and Electrical Equipment. – 2005. – Vol. 65. – P. 65-69. (In Russian).
- **11. Zhiznjakov A.L.** Allocation and analysis of edges and skeletons of halftone images using multiresolution representation. // Digital science magazine "Issledovano v Rossii" [Electronic resource]. – 2006. – URL: <http://zhurnal.ape.relarn.ru/articles/2006/150.pdf> (request date 14.02.2015). (In Russian).
- **12. Solnceva M.O., Kuharenko B. G.** Application of node clustering algorithm on graphs with sparse adjacency matrix.// Trudy MFTI. – 2013. – Vol. 5(3). – P. 75-83. (In Russian).
- **13. Dubinin D.V.** Evaluating the quality of edge detector algorithms on images approximated by homogenous Markov fields / Laevsky V.E., Kochegurov A.I. // Bulletin of the Tomsk Polytechnic University. – 2010. – Vol. 9(3). – P. 130-134.
- **14. Mesteckij L.M.** Skeletonization of a multiply-connected polygonal domain based on its boundary adjacent tree // Sib. zhurn. vychisl. matematiki / RAN. Siberian branch. – Novosibirsk. – 2006. – Vol. 9(3). – P. 201-216. (In Russian).
- **15. Gudkov V.Ju.** Methods for mathematical description and identification of fingerprint.// Trudy ISA RAN. – 2008. – Vol. 38. – P. 336-356. (In Russian).
- **16. Shcherbakov M.A.** Nonlinear filtering with adaption to local properties of the image / Panov A.P. // Computer Optics. – 2014. – Vol. 38(4). – P. 818-824. (In Russian).
- **17. Ilyasova N.Yu.** Computer technology for the spatial reconstruction of the coronary vessels structure from angiographic projections / Kazansky N.L., Korepanov A.O., Kupriyanov A.V., Ustinov A.V., Khramov A.G. // Computer Optics. – 2009. – Vol. 33(3). – P. 281-317. (In Russian).

