https://doi.org/10.32603/1993-8985-2019-22-3-24-35
УДК 004.931; 004.932

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IMAGE SEGMENTATION AND OBJECT SELECTION BASED ON MULTI-THRESHOLD PROCESSING

Abstract
Introduction. *In order to automate data processing in remote observation systems using television and infrared cameras, synthetic aperture panoramic radars, as well as laser and acoustic systems, it is essential to be able to reliably detect, isolate, select and localise objects of various shapes in images.*
Objective. *The development of a methodology based on multi-threshold analysis.*
Materials and methods. *The developed image segmentation and object selection approach having optimal selection threshold assessment is based on the results of multi-threshold image analysis.*
Results. *Based on the analysis of a series of standard objects with known shapes hindered by synthetic noise, as well as representative examples of remotely sensed images of the Earth's surface, improvements in the characteristics of both entire image segmentation and selection of particular objects according to several objective criteria were achieved.*
Conclusion. *The main advantage of the proposed approach consists in the minimisation of the post-processing shape modification of the selected objects. Although this is achieved at the cost of the resource-consuming multi-threshold analysis procedure for each processed image, this can be also partially compensated by the simplicity of the algorithm and its possible parallel implementation.*

Keywords: multi-threshold processing, image segmentation, object selection, binary integration method, statistical modelling

For citation: Volkov V. Yu., Markelov O. A., Bogachev M. I. Image Segmentation and Object Selection Based on Multi-Threshold Processing. Journal of the Russian Universities. Radioelectronics. 2019, vol. 22, no. 3, pp. 24–35. doi: 10.32603/1993-8985-2019-22-3-24-35

Acknowledgements. This work was supported by the Russian Science Foundation (research project № 16-19-00172- П).

Conflict of interest. Authors declare no conflict of interest.

Submitted 29.04.2019; accepted 20.05.2019; published online 27.06.2019

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СЕГМЕНТАЦИЯ ИЗОБРАЖЕНИЙ И СЕЛЕКЦИЯ ОБЪЕКТОВ НА ОСНОВЕ МНОГОПОРОГОВОЙ ОБРАБОТКИ

Аннотация.
Введение. *Задачи обнаружения, выделения, селекции и локализации объектов различной формы на изображениях неразрывно связаны с автоматизацией обработки информации в системах дистанционного наблюдения, использующие телевизионные и инфракрасные камеры, обзорные радиолокаторы с синтезированной апертурой, лазерные и акустические системы.*
Цель работы. *Разработка методики сегментации изображений и селекции объектов на них на основе многопороговой обработки.*
Материалы и методы. *Предложен подход к сегментации изображений и селекции объектов на них, основанный на выборе оптимального селектирующего порога с использованием апостериорной информации о результатах многопороговой обработки изображения.*
Результаты. *По результатам анализа серий модельных объектов заранее известной формы в условиях добавления синтезированного шума, а также репрезентативных примеров реальных изображениях, полученных при дистанционном зондировании поверхности Земли, показано, что за счет использования результатов многопороговой обработки удается улучшить характеристики как сегментации изображения в целом, так и селекции объектов по ряду объективных критериев.*
Заключение. *К достоинствам предложенного подхода следует отнести минимизацию искажений формы селектируемых объектов в ходе обработки изображения. Платой за это является ресурсоемкость процедуры многопороговой обработки для каждого анализируемого изображения, что отчасти может быть компенсировано простотой алгоритма и возможностью его параллельной реализации.*

Ключевые слова: многопороговая обработка, сегментация изображений, селекция объектов, метод бинарного интегрирования, вероятностные модели

Для цитирования: Волков В. Ю., Маркелов О. А., Богачев М. И. Сегментация изображений и селекция объектов на основе многопороговой обработки // Изв. вузов России. Радиоэлектроника. 2019. Т. 22, № 3. С. 24–35. doi: 10.32603/1993-8985-2019-22-3-24-35

Источник финансирования. Работа выполнена при поддержке Российского Научного Фонда (исследовательский проект № 16-19-00172-П).

Конфликт интересов. Авторы заявляют об отсутствии конфликта интересов.

Статья поступила в редакцию 29.04.2019; принята к публикации 20.05.2019; опубликована онлайн 27.06.2019

Introduction. The detection, isolation, selection and localisation of variously shaped objects represented in images is an essential function for a variety of applications. Computer imaging systems utilising television and infrared cameras, synthetic aperture radar (SAR) surveillance systems, as well as laser and acoustic remote sensing systems, are prominent examples of such applications. Such methods permit the solution of problems including object identification, tracking and matching as well as combining information from images obtained from different sources [1].

Under contemporary business conditions, classification research in the area of terrestrial and aquatic environments is widely carried out using remote sensing systems. The main aim of the processing of acquired data is the extraction of information from the image and transformation of the content into knowledge. The images obtained by the remote sensing systems must be automatically converted into structured information capable of being used in combination with other data, typically within the framework of the widely used Geographical Information System (GIS) [2], [3].

Generally, the objects of interest are more compact and exhibit more regular structure in comparison with the background. Variety and instability of object shapes and textures, as well as intense non-stationary background determines processing complexity. Low signal-to-background ratios usually characterise the areas of the object of interest. In addition, the registered digital image may be of low quality, as well as possessing a small number of quantisation levels, non-stationary characteristics and fuzzy object structure boundaries, for example, natural and artificial structures (rivers, roads, bridges, buildings). A random background of such systems differs from Gaussian noise; probability densities are considerably asymmetric, while their asymptotic forms are characterised by either lognormal or contaminated-normal tails. It is difficult to perform a unique identification of such densities in the case of discrete sampling.

The background could also contain elements that are structurally similar to the signals. Such background characteristics make the application of most known adaptive threshold-based processing methods inefficient due to the absence of representative homogeneous areas that could be used for threshold estimation. An incorrect threshold identification can lead to a loss of the useful objects at the first stage. Other problems include low quality of the sensed images, as well as the presence of blurs, fuzzy boundaries; moreover, SAR images suffer from serious internal speckle noise [4].

The necessity of integrating data from various sources within specialised GIS frames into modern remote sensing systems leads to the importance of a translation of initial raster images to structured (objected or featured) image representation

Traditional segmentation schemes use characteristics extracted from the raw images, which indirectly take the properties of the object of interest into account. In particular, properties of the raw image histograms are widely used in combination with boundary properties. On the other hand, results of the following selection of the objects of interest are rarely used for segmentation [5]–[13]. It should be noted that, according to the classic definition, the image segmentation assumes the assignment of each pixel to a unique object. However, in a more general scenario, objects may overlap, leading to the assignment of some pixels to several objects simultaneously.

Typically, the homogeneity of some parameter could be used as a feature for the segmentation of the image into separate objects with total intensity or intensity in a single colour channel being prominent examples. Such areal methods are generally based on the assumption that neighbouring pixels within the same isolated area exhibit close values of the classifying parameter, for example, intensity [5].

There is currently a wide variety of object segmentation methods for various applications of image analysis, not only in the remote sensing systems but also in other data analysis systems, for example, microscopic and biomedical visualisation [14], [15].

For a detailed review of modern image segmentation methods, we refer to [5] where four categories are distinguished based on the key elements used for segmentation: 1) pixels; 2) boundaries; 3) areas; 4) other. The first category includes the method of threshold processing and clustering, while the second uses boundary detectors. The third category comprises the watershed method, splitting and merging, levels sets and active contours. Finally, the fourth category is associated with the use of special techniques such as wavelets, neural networks and fuzzy sets.

The wide variety of available methods creates a problem of selecting the best algorithm for solving a given task under the condition of *a priori* uncertainty. This problem also complicates the reproducibility of results considering the number of the free input parameters, which are typically set by the user according to subjective criteria.

Each method has its own mechanism for incorporating prior information about the objects of interest. For example, the method based on area properties, the Fractal Net Evolution Approach (FNEA) and graph methods predominate in the creation of compact support areas of the employed object scales. The graph method is represented by four algorithms: Best Merge (BM), Minimum Spanning Tree (MST), Minimum Mean Cut (MMC) and Normalised Cut (NC) [5].

There are two main approaches for the formation of the object areas. One of these (the bottom-up approach) is based on the merging of small objects into larger ones according to the homogeneity of their properties (BM and MST). Another method (the top-down approach), in contrast, considers the initial image as an initial segment with its following fragmentation into separate parts based on their heterogeneity (MNC, NC).

Mentioned approaches are functional for the segmentation of the images obtained by the remote sensing systems (laser radars, SAR, multi- and hyperspectral, panchronic, etc.). However, there are important disadvantages. First of all, solutions for the appropriate procedures often exhibit high complexity since they require an optimisation problem to be solved, while a high processing rate is a typical requirement due to high quantity of reconstructed objects. In addition, the results obtained by the abovementioned methods essentially depend on the choice of the initial points for a solution sequence, often leading to the dependence of the result on a change in the initial conditions.

One approach to reducing the influence of these factors and thus overcoming their disadvantages is to consider the specific features of the objects to be selected, e.g. by introducing a separate learning stage, as well as by combining various methods [8]–[10]. All considered methods are based on the organisation of the image pixels into multiscale, hierarchic structures, which permit the selection of objects using various criteria. The task is to make this structure more explicit and simplify its application.

Therefore, the traditional segmentation schemes use the characteristics distinguished from the initial images, taking the properties of the object of interest into account indirectly. In particular, the following image properties, which depend on the principles of image formation, are widely used: initial image histograms, properties of the segmentation area boundaries (intensity variation) and contours of separated objects. On the other hand, the results of the following object selection processes are rarely used for segmentation.

The multi-threshold processing. In this paper the segmentation methods using a multi-threshold processing are considered. Such processing transforms the initial monochrome image into a set of binary (layers). In the case of sufficiently high number of thresholds it is possible to neglect the information loss. At the same time, processing of the binary images is easier and faster than multilayered images.

By merging the binary layers, the area occupied by each object would decrease with increasing the threshold level that should be taken into account. As a result, three-dimensional hierarchic structure, in which each object occupies some volume, is created. In some cases, a single pixel from the image could be assigned to several objects. Further selection is carried out using various geometric criteria. Object selection results for each threshold value could be used for an adaptation of the threshold levels and for the final segmentation of the image.

Various applications of the multi-threshold processing aimed to the image segmentation are considered in the numerous papers (see, for example, [1], [9]–[13]). In general, the multi-threshold segmentation is based on the properties of the initial image intensity histogram. In the most cases, the last step is the choice of the unique (global) optimal threshold value, whereas it is often necessary to set the local thresholds for each object separately. At the same time, the properties of the objects of interest and the results of their selection are not considered.

It is necessary to describe the expected results in order to implement the selection. The main assumptions here are the coupling of the pixels in the area of the object of interest and the isolation of one object from the others. As a rule, other than the typical dimensions and various assumptions concerning its area, perimeter, shape and orientation, information about the object is lacking.

An alternative approach is to select and define the optimal threshold value according to the criterion of maximum of the object count histogram and / or the total area occupied by the objects, which is brought into the required area range according to the preliminary object selection for many threshold test values. This approach has been proposed in papers [14], [15] for the selection of small-scale objects. It is effective in the presence of multiple objects having similar characteristics within the analysed image and when the choice of the best threshold is based on sufficient statistical information. In contrast, when identifying small samples, it is preferable to carry out a histogram analysis of the total area.

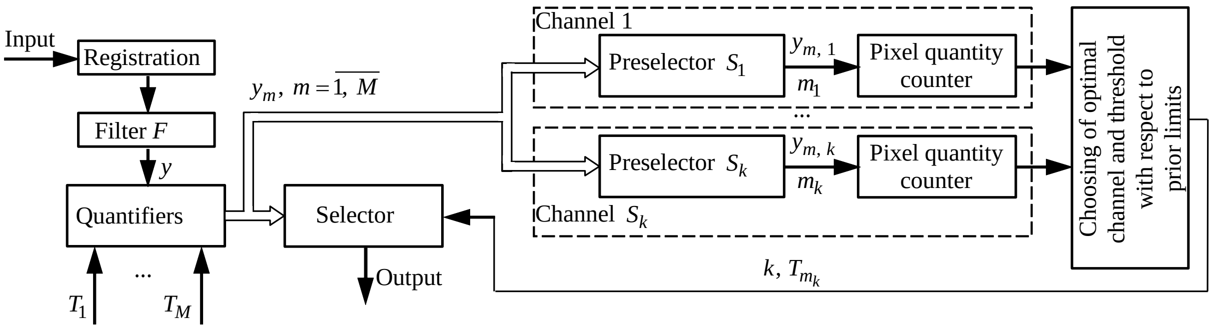

Fig. 1. Algorithm of selection of objects by area

The development of this idea is connected to the shape-based object selection approach. In cases when the above method does not allow the best threshold to be selected, the easiest way is to choose one of the local histogram extremes. An additional geometric parameter – for example, the ratio of the perimeter square to its area or the ratio of the ellipse main axis square to its area – is then used as the additional criterion. The proposed method may be used for the selection of specific types of cells in microscopic images or biological material sections [16], [17].

The further development of the described approach presented in this paper includes an estimation of the geometrical parameters of the objects on all binary images following multi-threshold processing and selection using a specified geometrical parameter. The optimal threshold value is selected using the extremum of the estimated parameter.

Let us consider the method of object selection according to its area. The applied method is analysed in detail according to the test images and on the images registered by the remote sensing systems.

Object selection by area. In the case of application of this type of selection, the coupling of neighbouring pixels on binary image I_T is considered as the primary property that distinguishes the object of interest from the noise background. First, let us consider the analysis approach based on global threshold selection.

Fig. 1 shows the structure of the areal object selection algorithm. A filter F performs preliminary smoothing of the input image for the elimination of high frequency noise. Quantifiers form M binary layers, obtained using the thresholds T_m, $m = \overline{1,\ M}$, and analysed by a set of k channels. Each channel is tuned to the range of isolated objects areas S_k, $k = \overline{1,\ K}$, which includes a preselector of these objects and a counter that enumerates the number of the defined objects as well as the pixels assigned to the object. As a result of the adaptation, the threshold values T_{m_k} are selected for each channel, i.e. that unique binary layer in which the objects with specified areas can be most accurately selected. The result containing the maximum of the pixels assigned to the objects is chosen amongst the obtained channel results. The channel number and the threshold value are then transmitted to the output selector that in turn performs the final selection according to the selected parameters.

Fig. 2 shows a noisy monochrome test image with dimensions of 256×256 pixels. The image contains rectangular objects with dimensions 20×8, 20×16, 20×32 and 20×64 pixels with the area of the smallest one 160 pixels.

Let us introduce the concept of a contrast signal-to-noise ratio for characterisation of the difference between objects and background. The contrast is defined as the difference between the average intensity

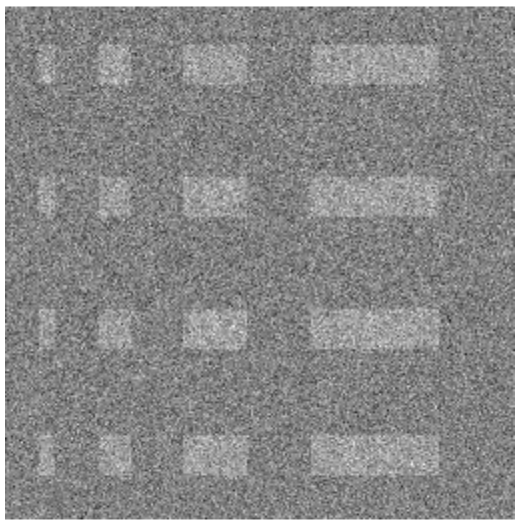

Fig. 2. Test monochrome noisy image

of the pixels assigned to the object and to the background, respectively: $K = \bar{B}_{\text{obj}} - \bar{B}_{\text{g}}$. Then the contrast signal-to-noise ratio is $d = K/\sigma$, where σ is the root-mean-square deviation of the noise. Objects on the test image on Fig. 2 have a low signal-to-noise ratio $d = 1.163$ in each signal pixel that corresponds to $\bar{B}_{\text{g}} = 110$, $\bar{B}_{\text{obj}} = 145$, $\sigma = 30$.

Fig. 3 shows the results of the single-threshold selection of the coupled objects following elimination of the small objects for three different threshold levels: high $T = 130$ (*a*), middle $T = 123$ (*c*), and low thresholds $T = 109$ (*d*). The areas of the selected objects are denoted by pseudocolours. The areas of the objects (the count of pixels assigned to it) in Fig. 3, *a*, *c*, *d* is shown by the pseudocolours (grayscale).

Assignment of the neighbouring background pixels to the objects is observed with a decrease in the threshold (Fig. 3, *c*). This leads to the formation of "branches" and their further expansion, with neighbouring objects merging and forming conglomerates. In this case, it is possible that the number of useful objects might decrease. Additionally, some false objects, with areas comparable to those of the objects of interest, can be observed. The dependence of the numbers of the selected objects on the threshold value is shown in Fig. 3, *b*.

There are two types of distortion depicted in Fig. 3: the loss of the pixels in the object area and the addition of extra pixels attached to their boundaries. Objects of interest lose some pixels when the threshold value is high, which is necessary in order to reduce the number of false objects. In the case of low

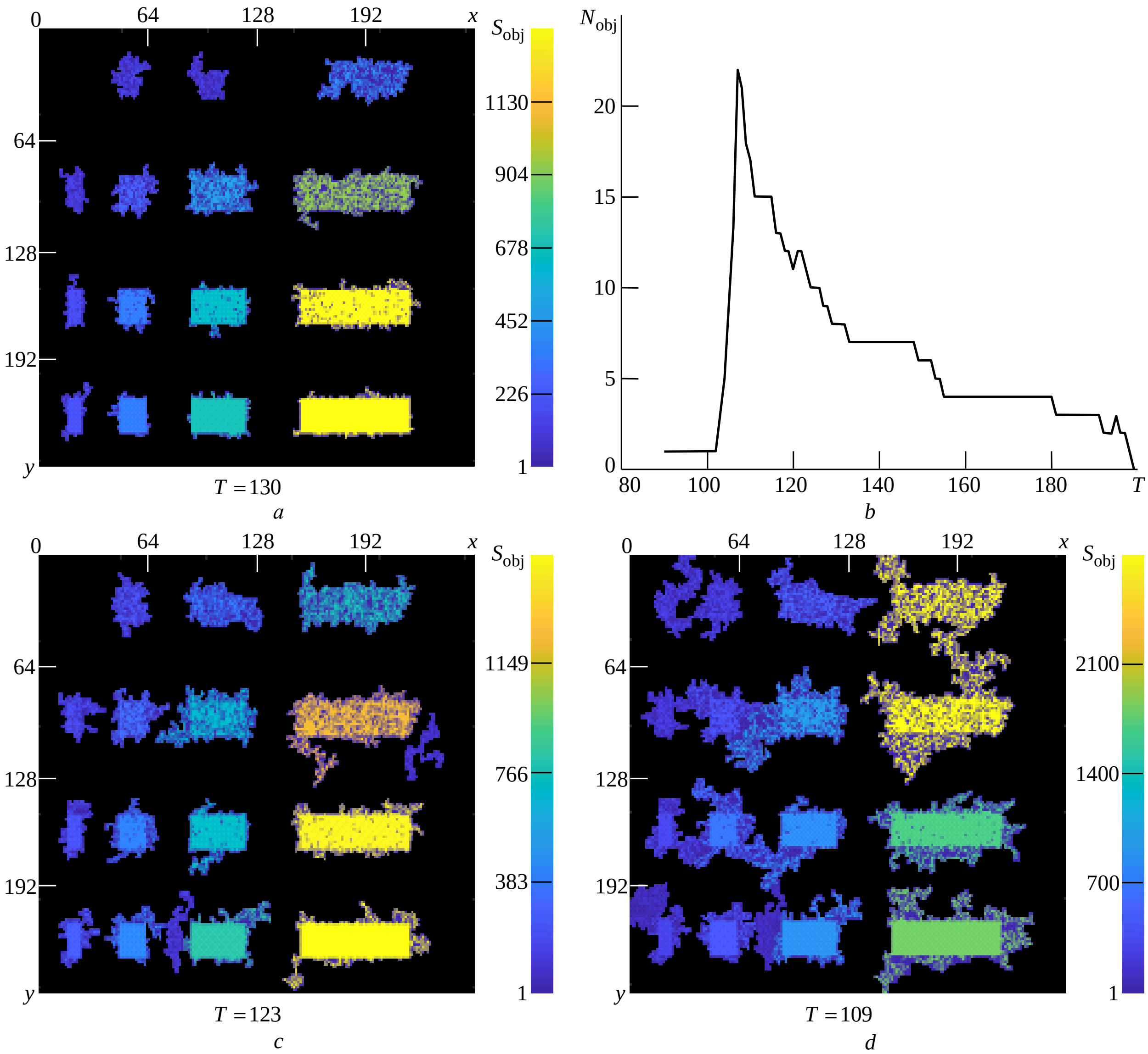

Fig. 3. Single-threshold selection of connected rectangular objects

signal-to-noise ratio, the boundaries of the useful objects are sufficiently deformed. The boundaries often exhibit fractured shapes. This leads to a noticeable increase in the perimeter of these coupled fragments.

The optimal threshold must provide acceptable preservation of the a priori known shapes of the useful objects. In particular, it is possible to require approximate parity of the quantity of pixels that are lost within the object with the quantity of the pixels that are assigned to its boundaries. In this case, the optimal threshold does not correspond to the maximum number of selected objects in the specified area, but is shifted to higher values. Fig. 3 indicates that the condition of approximate parity of lost and assigned pixel quantities is satisfied at $T=130$ (Fig. 3, *a*); however, the maximum quantity of the objects is achieved at $T=109$ (Fig. 3, *d*).

Considering a less favourable case, when the intensity values of the image pixels are mutually independent, it is possible to calculate the effectiveness of the object detection in the specified area *S*, which includes n pixels, in approximation of uniform background. If the binarisation threshold is high enough, then it is possible to ignore the small quantity of background pixels attached to the object boundaries. Thus, the object of interest could be selected against a noisy background by the fixation of k threshold exceedances from *n* available in the area *S*, and comparison of *k* statistics with the counting threshold *m* (the binary integration method) [17].

The binary integration method is based on the summation of the number of threshold exceedances within a sliding window of given size. The statistics of *k* is distributed in accordance with the binominal law within each position of the sliding window. The probability of achieving or exceeding of the threshold k_T according to the statistics of *k* is given by the well-known formula:

$$P\left(k \geq k_T\right) = \sum_{k=m}^{n} C_n^k p^k \left(1-p\right)^{n-k}, \qquad (1)$$

where C_n^k – the binominal coefficients; *p* – the probability of exceedance in each pixel. In the noise area $p = p_0$, as well as in the object area $p = p_1$, it is assumed that $p_1 > p_0$. Since the binominal distribution could be approximated by the Gauss distribution, it is possible to introduce a deflection for the decision statistics

$$dk = \sqrt{n}\left(p_1 - p_0\right) \Big/ \sqrt{p_0\left(1-p_0\right)}$$

as the ratio of the statistical expectation value of intensity within the object to the root-mean-square value of the noise. In the case of binary integration, the statistics of k has statistical expectation value $m = np$ and variance $\sigma^2 = np\left(1-p\right)$. Therefore, the statistical expectation is changed within the object area along with the variance of the decision statistics.

During the selection process, it is possible to decrease the probability p_0 and, consequently, decrease the binary threshold for achieving the previous false alarm probability. With an increase in the values of p_1 within the object area, the processing efficiency also increases. However, since only coupled objects are selected and their quantity is sufficiently lower than the number of *k*-combinations of *n* elements, the statistics of *k* does not follow the binominal distribution.

By the same idea as in the case of the binary integration, the probability of achieving or exceeding threshold k_T by the statistics of k could be written as

$$P\left(k \geq k_T\right) = \sum_{k=k_T}^{n} B_n^k p^k \left(1-p\right)^{n-k},$$

where B_n^k are the coefficients denoting the number of the coupled objects consisting of *k* pixels in the area of *n* pixels. By now, the values of these coefficients are obtained only for a one-dimensional model and rather small numbers of objects $n \leq 9$ [18].

Comparative analysis of the methods. According to Formula (1), the probability calculation is not sufficiently complex to derive the precise value of the decision threshold. However, this could instead be achieved iteratively by means of an adaptive algorithm. The selection of the objects by their areas with respect to the object shape deformations limits is used for the adaptive adjustment of the threshold. Here, the control of the shape of the objects and their boundaries could be achieved using various formalised properties; among these, the area compactness [1] $P_S = P^2 / \left(4\pi S\right)$, should be highlighted, where *P* is the object perimeter, while *S* is its area.

Fig. 4 shows the simulation results. The test image (Fig. 4, *a*), which contains 49 square objects having an area of 16×16 px, is hindered by the additive Gaussian noise. Figure 4, *b* shows the dependence of the number of the selected objects on the threshold value. The results of the selection by the object area are represented in Fig. 4, *c* $\left(S_{\min} = 120 \text{ pix.}\right)$, while the results of the object selection by the binary inte-

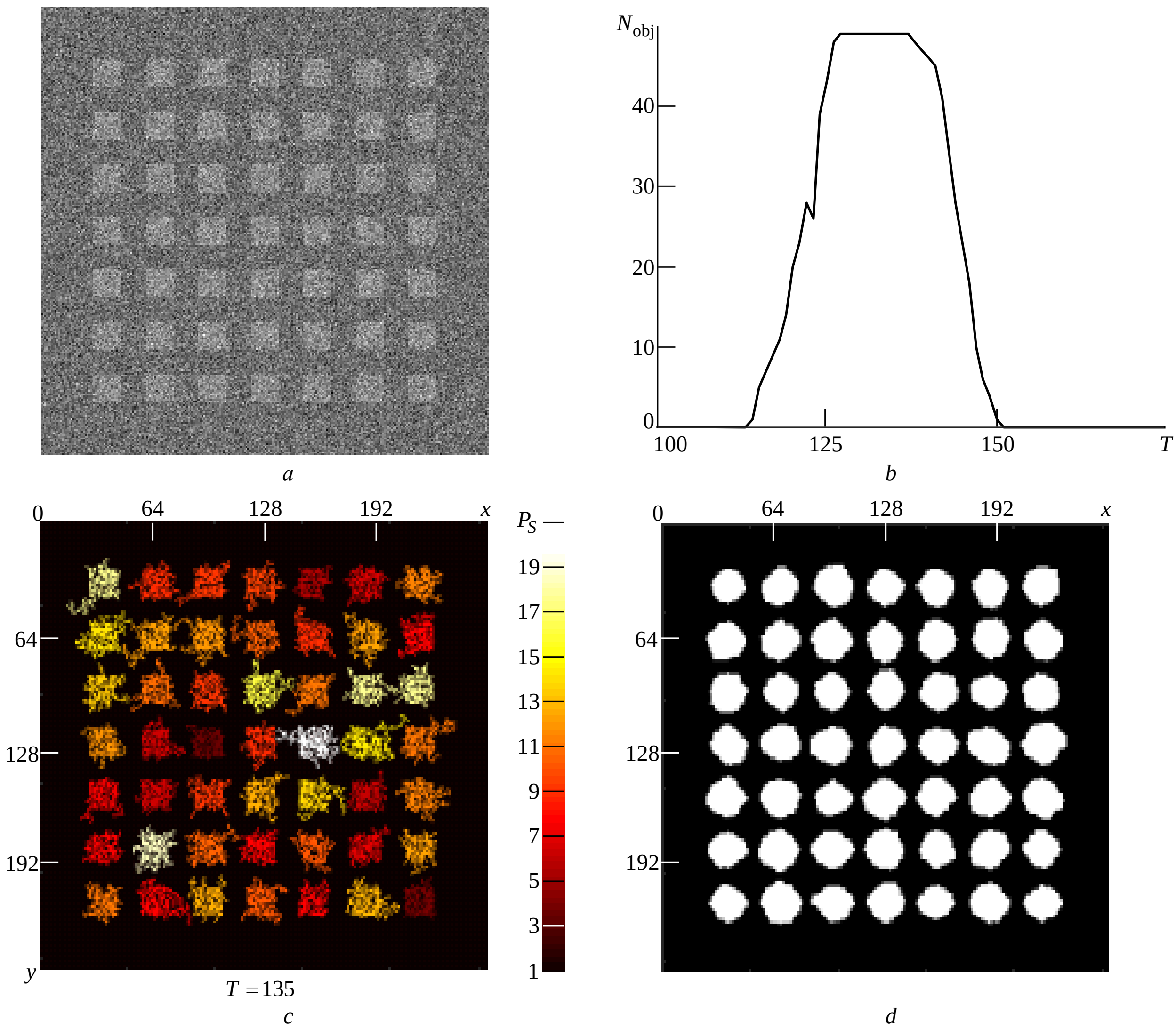

Fig. 4. The results of modeling the selection of objects

gration method are shown in Fig. 4, *d*. The contrast signal-to-noise ratio in each pixel is $d = 1.163$. In the case of the selection of an object by area, acceptable deformation of the object boundaries is achieved at the threshold values higher than $T = 135$. At lower threshold values, the shapes of the objects are sufficiently deformed by the additive noise, including destruction of the boundaries. As is seen in Fig 4, *d*, the binary integration method is optimal for the improvement of the noise-robustness, while leading to inevitable object deformations; nevertheless, the proposed method acceptably reconstructs the shapes of the objects of interest.

Fig. 5 shows the results of the selection of objects by their areas in a sample frame of a television aerial image (*a*), the dependence of the number of coupled objects on the threshold value (*b*), as well as the results of the selection of objects by their areas at various threshold values: $T = 94$ (Fig. 4, *c*), 128 (Fig. 4, *d*), 145 (Fig. 4, *e*), and 154 (Fig. 4, *f*). The quantity of the defined objects is $N_{obj} = 40$, 33, 31 and 28, respectively. Pseudocolours (grayscale) denote the object areas. Fig. 5, *c* corresponds to the maximum number of the selected coupled objects.

Increase of the threshold allows the object resolution to be increased (Fig. 5, *d*), but at the same time fewer intensive objects disappear. If the objects are isolated, then each of them is localised following selection, i.e. the coordinates of their centres, as well as other shape and texture parameters, are evaluated.

The disadvantage of the selection of objects by their areas is the requirement that their area parameters be specified in absolute values (pixels), which is complicated in the case of variable image scales. This method performs poorly when the background is non-homogeneous, leading to false detections of objects with similar areas to those of the objects of interest (Fig. 5, *c* and *d*).

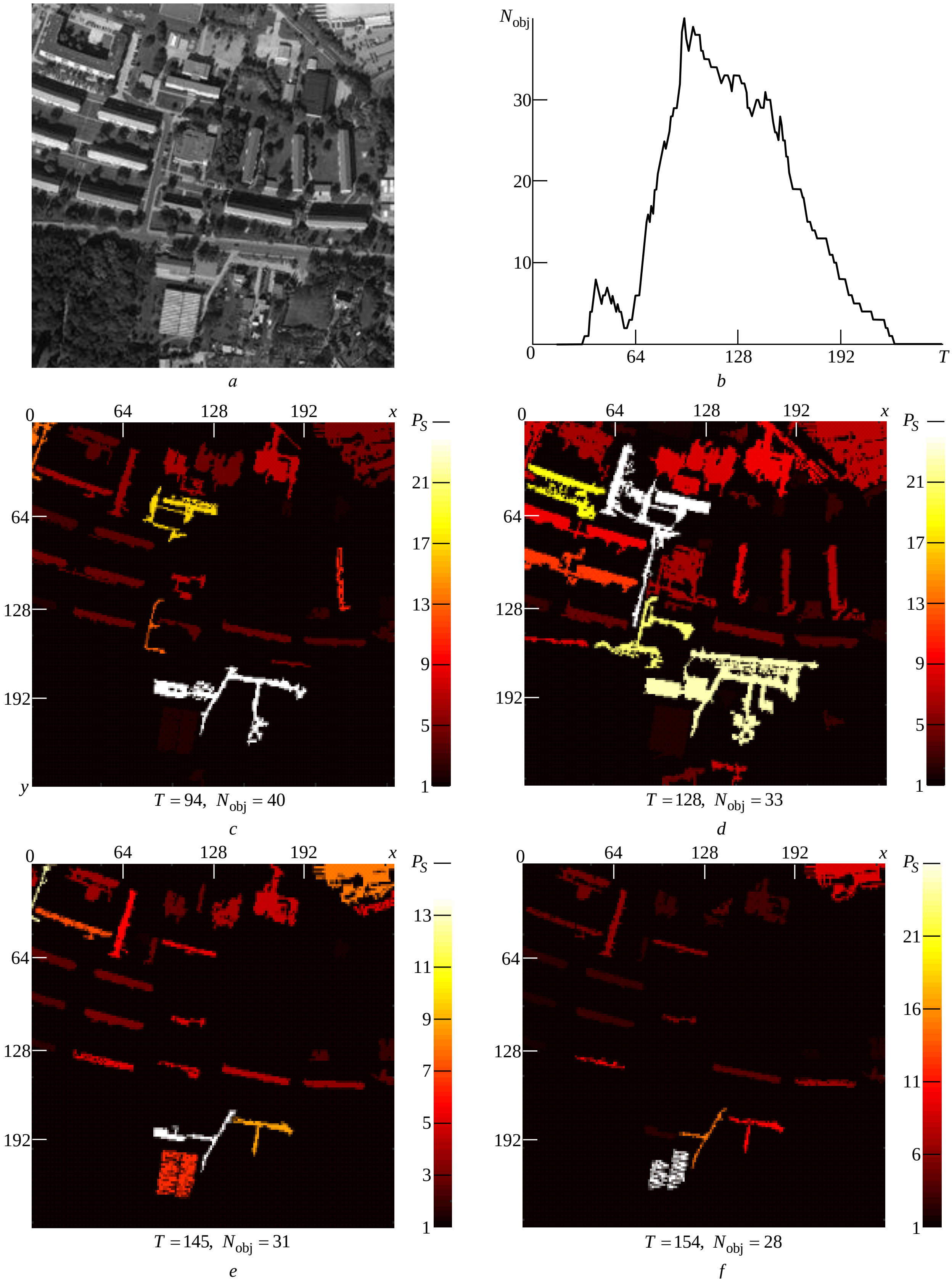

Fig. 5. Selection of objects by ar ea on the frame of the television aerial image

Conclusion. An approach based on preliminary multi-threshold image processing and the selection of isolated objects in binary layers with further adjustment of the optimal threshold based on the selection results is proposed. By using the threshold adjusted according to the results of the selection, it is possible to improve the characteristics of the entire image selection procedure as well as the selection of objects using various criteria such as the preservation of the shapes of objects using the *a posteriori* information. The cost for this is the high computational complexity of the multi-threshold processing, which could be partially compensated by the simplicity of the algorithm and the possibility for its parallel implementation.

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