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An Optimization of System for Automatic Recognition of Ischemic Stroke Areas in Computed Tomography Images

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Abstract. The paper considers application of stochastic optimization to system of automatic recognition of ischemic stroke area on computed tomography (CT) images. The algorithm of recognition depends on five inputs that influence the results of automatic detection. The quality of recognition is measured by size of conjunction of ethalone image and the image calculated by the program of automatic detection. The method of Simultaneous Perturbation Stohastic Approximation algorithm with the Metropolis rule has been applied to the optimization of the quality of image recognition. The Monte-Carlo simulation experiment was performed in order to evaluate the properties of developed algorithm.

Key words: ischemic stroke area, Monte-Carlo method, computed tomography.

1. Introduction

The most of algorithms for image processing strikes with snag of determination of internal parameters that regulate the quality of results. There is always a problem in choosing the values of empirical parameters and motivation of the values chosen. It was the same with the algorithm for system of automatic recognition of areas of ischemic stroke in CT images (Grigaitis *et al.*, 2004). In this paper, the optimization algorithm is described, that gave the values of parameters by definite criteria. We have developed an optimization algorithm (Bartkutė *et al.*, 2006; Bartkutė and Sakalauskas, 2007) for system of automatic recognition of ischemic stroke areas (Grigaitis *et al.*, 2004; Bernatavičienė *et al.*, 2007). The target of this system were CT images of human brain (Fig. 1) where ischemic stroke has dark features with texture property similar to other dark areas (Novelline and Squire, 1987).

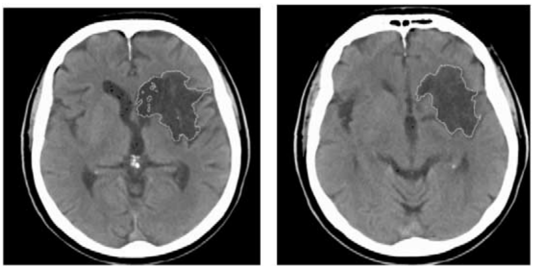


Fig. 1. The examples of automatically detected stroke areas.

The system that recognizes stroke areas have 16 different functions and is designed for 8 bit images converted from CT. Most of these functions are complicated themselves and they have several parameters that influence directly the results of recognition. The main problem solved in the paper – the search of values of parameters that ensure the best results of automatic recognition.

2. The Algorithm for Automatic Recognition

Consider that recognition system has 32 parameters with their intervals from 1 to 10. Then amount of possible combinations is 10^{31} and calculations of all combinations would last the years. By this reason optimization algorithm must be used to optimize the values of parameters. For testing of designed optimization algorithm we used 5 functions and their parameters x_1, x_2, x_3, x_4, and x_5 that have the most great influence on the results. Fig. 2 illustrates the principle of operation of recognition system. The parameter x_1 regulates the size of sliding window of average linear filter, that reduces noise level in images. This parameter has only four values. The second parameter x_2 is associated with detection of gyri areas in human brain image. This parameter has interval from 1 to 16. The

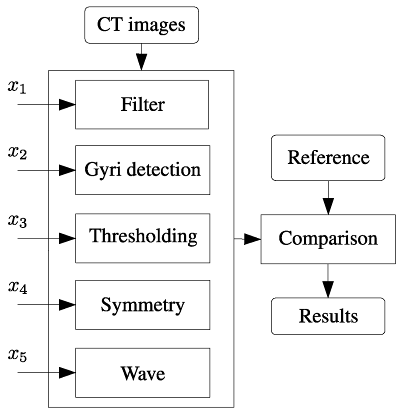


Fig. 2. Basic flowchart of principle of optimization of recognition system, where x_1, x_2, x_3, x_4, and x_5 are regulated parameters.

third parameter x_3 regulates threshold level for images. It regulates treshold level from 50 to 110 with 13 steps. The fourth parameter x_4 is related with symmetry filtering and regulates the level of comparison of two hemishperes of human brain and has 19 steps. The last x_5 parameter regulates the capability to select the ischemic stroke area, it has 12 steps. So, we have 189696 possible combinations of values of parameters.

2.1. *The Filtering*

The initial filtering is neccessery for Roberts Cross edge detector, thresholding, and region of ischemic stroke selection. For this purpose the images $f(x, y)$ are filterred by linear filter. The linear spatial filter is simply averaging the pixels contained in the neighborhood of the filter mask. This filter sometimes is called averaging or low pass filter and is described by formula:

$$I_{center} = \frac{1}{k^2} \sum_{m=1}^{k} \sum_{n=1}^{k} i_{mn}; \tag{1}$$

I_{center} is the average value of pixels values in center of sliding window, k is width of sliding window, i_{mn} is a value of pixel in nth row and mth column of sliding window. The average filter is regulated by x_1 parameter that has four values of sliding window width $k = 3, 5, 7, 9$.

2.2. *Detection of Gyri Areas*

The most complicated problem of detection of ischemic stroke is elimination of gyri areas of human brain on CT images (Grigaitis *et al.*, 2004). There are two reasons of complexity: first is that brightness values of stroke are similar to the brightness of gyri areas; second is that ischemic stroke areas have similar sizes to ordinary gyri areas. Difference between such areas is that gyri areas mostly look like tremulous stripes (Mangin *et al.*, 2004) and they can be selected according this property. For this purpose gradient edge detector is used. We chose Roberts cross method that gave similar results to other edge detectors such as Canny or Laplace (Gonzalez and Woods, 2002). The gradient of brightness of image at specific location x, y is defined as

$$\triangledown f = \Big(\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y}\Big). \tag{2}$$

Chosen edge detector used only one 2×2 sliding window. An example of edge detection on grey level CT image is shown in Fig. 3 (b). Assume that gyri areas are $g(m^*, n^*)$, then detection procedure is described as erosion-dilation and threshold combination:

$$g(m^*, n^*) = \gamma\big((f(x, y) \oplus \alpha) \ominus \alpha\big), \tag{3}$$

where γ is a threshold level coefficient, α is a structuring element of dilation and erosion.

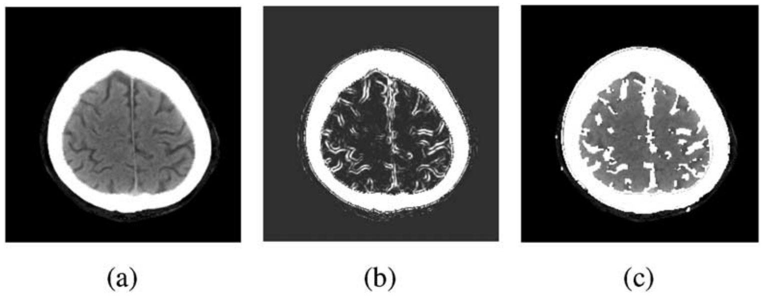


Fig. 3. The examples of edge detection: initial image (a); processed image (b); complete detection of gyri areas (c).

The dilation and erosion were used as filter to extract gyri areas and reduce noise (Grigaitis *et al.*, 2004). For optimization purpose the threshold coefficient γ is associated to the parameter x_2 that has sixteen steps. They regulate the threshold interval from 100 to 255, such values possess a lot of pixels of gyri areas (Fig. 3 c).

2.3. *The Threshold of Histograms*

The threshold of gray level images helps to extract approximately the areas that contain ischemic stroke properties. This can be called extraction of region of interest (ROI) (Agraftotis *et al.*, 2003; Goktur *et al.*, 2001). Fig. 4 shows the histograms of areas of images that represent the objects of two types: gyri and ischemic stroke areas. Those areas were manually selected in 100 images, searching to determine the properties of objects.

Histograms 2 and 3 on Fig. 4 show interconnetion of brightness of pixels of stroke and gyri areas. Most pixels of the stroke area are approximately placed in interval from 63 to 140. Using this interval as ROI it is possible to reduce the area for detection of stroke and increase possibility that stroke will be detected correctly. The brightness of stroke areas have wide variation. Using threshold interval from 63 to 140 it is possible to select ROI areas, that have low size differences from analyzed images. It is shown (Fig. 5) that narrow interval of threshold yields differrently on various types of stroke areas. It is not always important, because final result strictly depends on other functions of recognition algorithm.

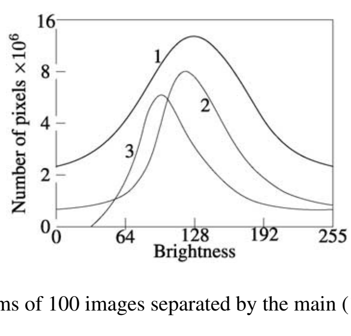
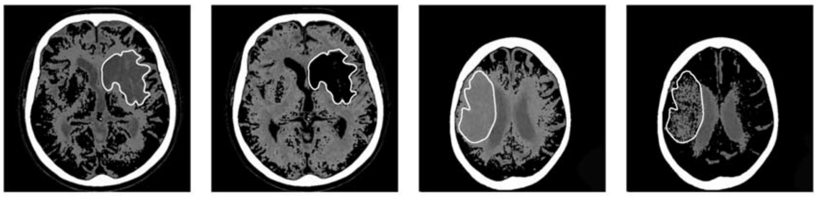


Fig. 4. An example of histograms of 100 images separated by the main (1), stroke (2) and gyri (3) areas.



(a) (b) (c) (d)

Fig. 5. The example of selection of stroke area using two intervals of threshold: correct selection (a); incorrect selection (b); correct selection (c); satisfactory selection (d).

The threshold of histograms is associated with the x_3 parameter and it has thirteen steps. The lower threshold limit varies from 50 to 128. The upper limits were selected admitting, that there is a lot of pixels brighter than 128, and sometimes they are in the stroke area.

2.4. *Symmetrical Comparison of Brightness of Pixels*

The most of ischemic stroke cases occur in brain nonsymmetrically. It is an advantage for comparison of hemispheres one with another. For this purpose the symmetry plane in CT image of human head must be detected (Grigaitis and Meilūnas, 2005). Assume that symmetry axis is vertical and has only one coordinate x'. Then hemispherical comparison for the left hemisphere can be defined:

$$I_k(x,y) = \begin{cases} 0, & \gamma_{symmetry}(I_l(x,y) < I_r(2x'-x,y)), \\ 1, & \gamma_{symmetry}(I_l(x,y) > I_r(2x'-x,y)). \end{cases} \tag{4}$$

For the right hemisphere:

$$I_k(2x'-x,y) = \begin{cases} 0, & \gamma_{symmetry}(I_l(x,y) > I_r(2x'-x,y)), \\ 1, & \gamma_{symmetry}((I_l(x,y) < I_r(2x'-x,y)). \end{cases} \tag{5}$$

Here $I_l(x,y)$ are pixels of image of the left hemisphere of human brain, $I_r(2x'-x,y)$ are pixels of image of the right hemisphere of human brain, $\gamma_{symmetry}$ is the parameter associated with x_4, and it regulates symmetrical comparison, x, y are the coordinates of pixels.

The comparison of hemispheres of human brain starts from determination of symmetry plane (Grigaitis and Meilūnas, 2005) that splits brain view into two hemispheres. Consider that hemispheres are symmetrical and linear noise filter was used, and the comparison procedure was implemented using Eqs. 4 and 5. As the basis for comparison the x' coordinate was calculated from symmetry plane for each CT slice. In the case when coordinates of pixels of the left hemishpere $I_k(x,y)$ are known, the coordinates of pixels of the right hemisphere are determined as $I_k(2x'-x,y)$. The results achieved by one variable $\gamma_{symmetry}$ are shown in Fig. 6. This variable is asocciated with the parameter x_4. The combination of trehsholding with symmetrical comparison can be used as mask

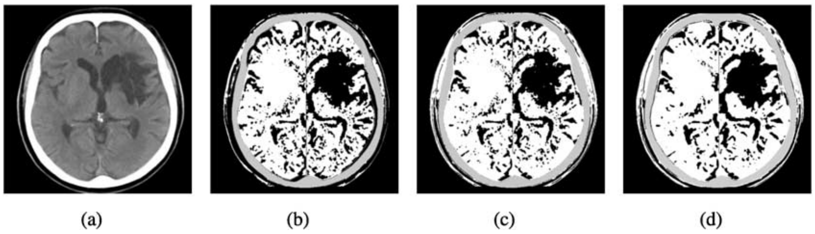


Fig. 6. The example of symmetrical comparison: initial image with symmetry axis (a); image of symmetrical comparison of hemispheres (b); combination of symmetrical comparison with thresholding (c); symmetrical comparison with filterred initial image (d).

for stroke area detection (Fig. 6 c). The benefit of linear filter is less noise on binary image (Fig. 6 d).

2.5. *The Wave Method for Area Selection*

The wave method is designed for selection of ischemic stroke area. For this purpose the initial points are used on any place of ischemic stroke area (Fig. 7 a). Designed algorithm derives these points automatically, but for analysis we can assume that we have several points p_t, where t is a serial number of point on stroke area Q. Using sliding window of size q_0 the standard deviation of pixels σ_0 (Gonzalez and Woods, 2002) is calculated in environment of the point (Fig. 7 b). This position of sliding window is initial. Then sliding window is shifted to x and y directions (Fig. 7 c) and the values of σ_j are calculated. If brightness of pixels in sliding window q_j satisfies condition $\sigma_j \leqslant \sigma_0$ then the pixels are the part of ischemic stroke area. The variable j shows the number of shifted sliding window q_j. The limitation of wave spreading is necessary in order to avoid the selection of areas that have similar properties as stroke area. For this purpose the mask formed in symmetrical comparison was used (Fig. 6 d).

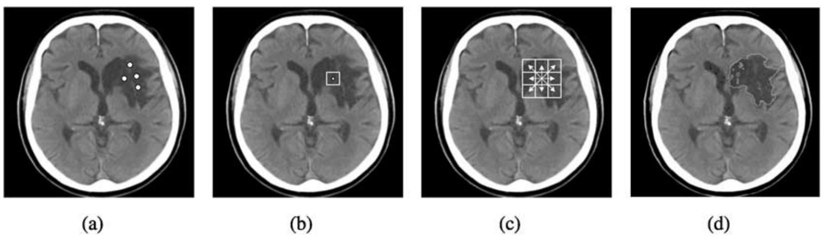


Fig. 7. The principle of selection of area of ischemic stroke: initial points on the stroke area (a); white square where dispersion of brightness of pixels is calculated (b); the other squares for comparison of dispersion (c); selected stroke area (d).

3. An Optimization of Aglorithm of System for Automatic Recognition of Ischemic Stroke Areas

An optimization of recognition algorithm concentrates on evaluation of the results varying the parameters x_1, x_2, x_3, x_4, x_5. The quality of the images can be described as the function $f(x)$, where $x = (x_1, x_2, \ldots, x_n)$ and $n = 5$. Empirical study shows that this objective function can be presented as smooth convex function disturbed by additive computational error. Let consider the modification of the Simultaneous Perturbation Stochastic Approximation algorithm with Metropolis rule for minimization of such function (Bartkutė *et al.*, 2006; Yang, 2000; Spall, 1992). Assume, the sequences are defined as $\rho_k = \min(a, \frac{c}{k})$ and $\sigma_k = \min(b, \frac{d}{k^2})$, $a > 0$, $b > 0$, $c > 0$, $d > 0$. These values are set before omptimisation and can be changed if desired results are not reached. The optimization algorithm is as follows.

Step 0. Assume that initial approximation x^0 and values of the parameters a, b, c, d be given, $k = 0$.

Step 1. Let the vector $\Delta^k = (\Delta_1^k, \Delta_2^k, \ldots, \Delta_n^k)$ consisting of Bernoulli variables, which take two values 1 or -1 with probabilities $p = 0.5$, be generated.

Step 2. Let two perturbed vectors $y^{2,k} = (y_1^{2,k}, y_2^{2,k}, \ldots, y_n^{2,k})$ and $y^{1,k} = (y_1^{1,k}, y_2^{1,k}, \ldots, y_n^{1,k})$ be computed:

$$y_i^{1,k} = \min\big(\max(x_i^k + \Delta_i^k \cdot C_k, x_{i\,\min}), x_{i\,\max}\big), \tag{6}$$

$$y_i^{2,k} = \max\big(\min(x_i^k - \Delta_i^k \cdot C_k, x_{i\,\max}), x_{i\,\min}\big), \tag{7}$$

where $C_k = \max(1, [\sigma_k + 0.5])$.

REMARK 1. If necessary values $y_i^{1,k}$, $y_i^{2,k}$ are taken as discrete numbers.

Step 3. Let two function values be computed: $z^{1,k} = f(y^{1,k})$, $z^{2,k} = f(y^{2,k})$. These values show precision of stroke area recognition.

Step 4. Let the point $\nu^k = (\nu_1^k, \nu_2^k, \ldots, \nu_n^k)$ be defined:

$$\nu_i^k = x_i^k + sign\Big(\frac{z^{1,k} - z^{2,k}}{y_i^{1,k} - y_i^{2,k}}\Big) \cdot W_k, \quad i = 1, 2, \ldots, n, \tag{8}$$

where $W_k = \max(1, [\rho_k \cdot |\frac{z^{1,k} - z^{2,k}}{y_i^{1,k} - y_i^{2,k}}|])$, $i = 1, 2, \ldots, n$.

Step 5. Let two perturbed vectors $y^{1,k} = (y_1^{1,k}, y_2^{1,k}, \ldots, y_n^{1,k})$ and $y^{2,k} = (y_1^{2,k}, y_2^{2,k}, \ldots, y_n^{2,k})$ be computed:

$$y_i^{1,k} = \min\big(\max(\nu_i^k + \Delta_i^k \cdot C_k, x_{i\,\min}), x_{i\,\max}\big), \tag{9}$$

$$y_i^{2,k} = \max\big(\min(\nu_i^k - \Delta_i^k \cdot C_k, x_{i\,\max}), x_{i\,\min}\big), \tag{10}$$

where $C_k = \max(1, [\sigma_k + 0.5])$.

Step 6. Let two function values be computed: $z^{1,k} = f(y^{1,k})$, $z^{2,k} = f(y^{2,k})$.

Step 7. Let the next approximation $x^{k+1} = (x_1^{k+1}, x_2^{k+1}, \dots, x_n^{k+1})$ be defined as follows:

$$x_i^{k+1} = \begin{cases} \nu_i^k, & \text{if } \eta \leqslant \mathrm{e}^{\frac{z^k - z^{k-1}}{T}}, \\ x_i^k, & \text{otherwise}, \end{cases} \tag{11}$$

where $T = 1, \eta$ is random variable uniformly distributed in the interval $[0, 1]$.

REMARK 2. If necessary values x_i^{k+1} are taken as a discrete numbers.

Step 8. Check the termination condition (for instance, $k \leqslant k_{max}$). If this condition is satisfied then stop the algorithm, otherwise $k = k + 1$ and go to *Step* 1.

REMARK 3. The final solution can be taken as the point with the best perturbed values $z^{1,k}$ and $z^{2,k}$.

REMARK 4. Other termination conditions can be introduced, say, using order statistics (Žilinskas and Zhigljavsky, 1991; Bartkutė and Sakalauskas, 2004) etc.

The proposed method was tested with function:

$$f(x) = \sum_{j=1}^{n} a_j \biggl((x_i - x_i^*)^2 + 0.1 \Bigl(1 - \cos\bigl(18(x_i - x_i^*)\bigr) \Bigr) \biggr), \tag{12}$$

where a_j is a set of real numbers, randomly and uniformly generated in the interval $[\mu, K], K > \mu > 0, n = 5$.

The samples of $T = 500$ test functions were generated, when $\mu = 2$, $K = 5$, $x_1^* = x_2^* = x_3^* = x_4^* = 0.5$, $x_5^* = 1$. The coefficients of sequence were chosen according to the convergence conditions (Bartkutė and Sakalauskas, 2007): $\rho_i = \min(10, \frac{1}{i})$, $\sigma_i = \min(10, \frac{1}{i^{\phi}})$, $\phi = 0.25$. Fig. 8 shows the averaged objective function under the number of iterations minimized by modificated SPSA is depicted. In Fig. 9 dependence of averaged values of variables $x_1^t, x_2^t, x_3^t, x_4^t, x_5^t$ on number of iterations t is illustrated. Presented figures show that the sequence x^t defined by the algorithm converges to the optimal solution.

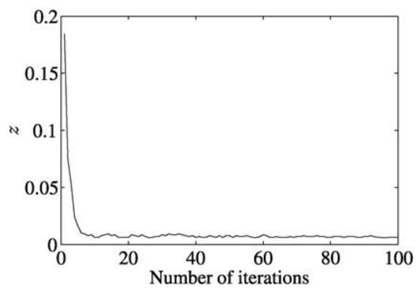


Fig. 8. Dependence of averaged objective function value on number of iterations.

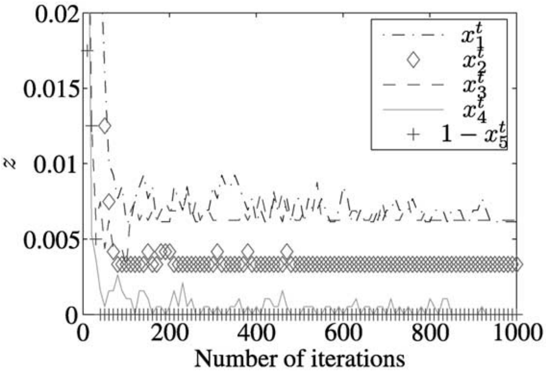


Fig. 9. Dependence of averaged values of variables $x_1^t, x_2^t, x_3^t, x_4^t, x_5^t$ on number of iterations t.

4. Experimental Results

Ischemic stroke recognition system calculates stroke areas on CT images, according x_1, x_2, x_3, x_4 and x_5 values. Processed images are compared with reference images using evaluation parameter z, that tends to reach 1.0 value when calculated stroke area matches to the reference:

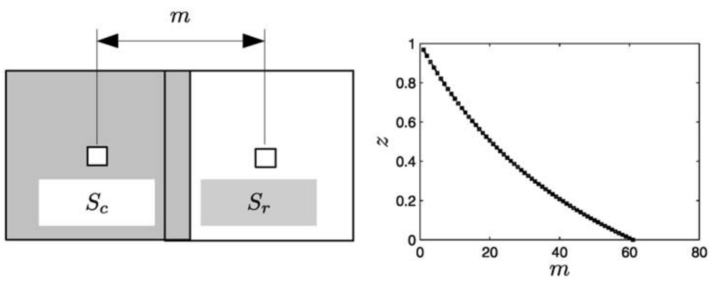
$$z = \frac{S_c \cap S_r}{S_c \cup S_r}. \tag{13}$$

Here S_c is a width of recognized stroke area, S_r – manually delineated reference image area.

The experiment with two simillar size squares show, that Eq. 13 is not linear because the value of fraction denominator can increase faster than numerator. In Fig. 10 is shown calculations of z parameter, here two intersected ojects named S_c and S_r are used. In changes of distance m the intersection parameter are calculated (Fig. 10 b). When objects' sizes are equal and intersected by 50% the evaluation parameter reaches 0.328 value. So the z parameter describes objects matching only.

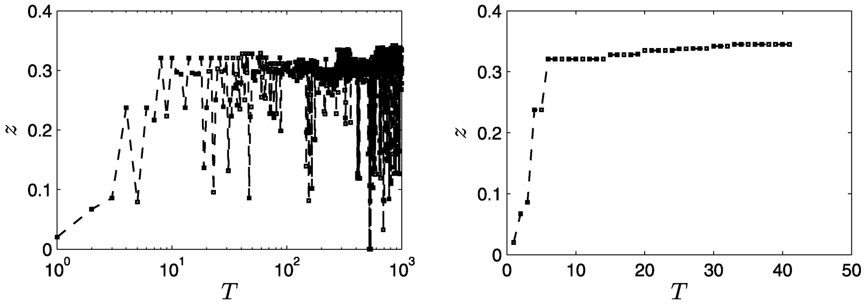
According optimization algorithm the vector $x = (x_1, x_2, \ldots, x_n)$ represents optimization parameters x_1, x_2, x_3, x_4, x_5. In the beginning they can be selected randomly or calculated using *Monte Carlo* method. In Fig. 11 an example of z values graph with random initial parameters is shown. The values of z at the beginning are small and increase with number of iterations (Fig. 11 a). After 100 iterations the z value can be compared with z value, that is calculated after 10^3 iterations. As seen in (Fig. 11 a) image the z value tends to decrease shortly. This happens because the optimization algorithm is designed to make search in variety of x_1, x_2, x_3, x_4, x_5 parameters where z definitely derives small values. Therefore, it is useful to separate the best values entire optimization process and collect it (Fig. 11 b). This graph shows increasing recognition quality entire optimization process.

In Fig. 12 is shown an example of detection of stroke area during optimization process. White curve represents automatically recognized area, black strips show manually



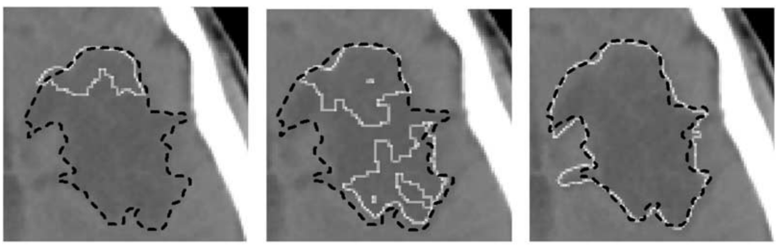
(a) (b)

Fig. 10. An example of evaluation parameter property: intersection of two objects 100×100 size with distance m (a); dependences of z on distance between objects in pixels (b).



(a) (b)

Fig. 11. Entire examination of values of optimization parameters: a) all z values are over 10^3 iteration; b) selected local maximums over examination.



(a) (b) (c)

Fig. 12. An example of IS area selection in optimization procecss: the area in the begining of optimization when $z = 0.096$ (a); the area after 5 iteration when $z = 0.24$ (b); the area after 8 iteration when $z = 0.35$ (c).

selected stroke area. In the beginning the random values of x_1, x_2, x_3, x_4, x_5 are used that give $z = 0.096$. After other iterations the z value increases. When z reaches its pseudo-maximum value the IS recognition algorithm becomes more precise and selects desired area (Fig. 12 c).

Consider that there are always complication in ethalon images with selected of IS areas and optimized algorithm cannot overpass it.

5. Conclusions

An optimization of ischemic stroke recognition algorithm for personal computers was analyzed. An adaptation of algorithm was based on comparison of initial images with reference images. The initial images with injured areas are retrieved by computed tomography device. The reference images are made manually selecting areas of stroke in each CT slice. In optimization process, change of initial parameters minimized difference between reference and initial images. The main recognition algorithm of stroke consists of 12 stages. Five parameters were chose to alter, that strongly affected the results of recognition. For optimization of discrete objective function the Simultaneous Perturbations Stochastic Approximation modification was used. Computer modeling with test functions showed that proposed algorithm reliably minimizes objective function. The results of investigation showed that proposed algorithm very fast finds optimum range of parameters and can be used for adjustment of robust images recognition algorithms.

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Ischeminio insulto sričių kompiuterinės tomografijos vaizduose automatinio atpažinimo sistemos optimizavimas

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Sprendžiamas stochastinės aproksimacijos optimizavimo uždavinys ischeminio insulto sričių automatiniam atpažinimui kompiuterinės tomografijos vaizduose. Atpažinimo algoritmas reguliuojamas penkiais įėjimo parametrais, kurie tiesiogiai įtakoja atpažinimo rezultatus. Atpažinimo kokybė matuojama sankirtos-sąjungos santykiu tarp etaloninių vaizdų ir atpažintų vaizdų. Opimizavimui naudojamas nuoseklios perturbacijos stochastinės aproksimacijos algoritmas leidžiantis optimizuoti vaizdo atpažinimą. Atlikti modeliavimo eksperimentai taikant Monte Karlo metodą, siekiant įvertinti sukurto algoritmo savybes.