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SEGMENTATION OF GRAYSCALE LOW-CONTRAST IMAGES USING FUZZY TRANSFORMS OF TYPE-2

Annotation. Segmentation of low-contrast grayscale images is a rather complex task due to the lack of a priori information about the location and characteristics of objects of interest that can be compared with noise. To solve this problem, various fuzzy algorithms based on the processing of membership functions to fuzzy sets describing the analyzed properties are currently often used. The paper proposes the algorithm for segmenting halftone images based on the iterative application of type-1 and type-2 fuzzy transformations. The presented algorithm provides sufficient image segmentation for visual analysis, without allowing excessive detailing, and has a small number of control parameters that do not require lengthy tuning. Unlike the fuzzy clustering algorithms, it does not use the fuzzy cluster center matrix, which reduces the computational load. Experimental results are presented on the example of real grayscale medical images segmentation.
Keywords: low-contrast images, fuzzy methods, visual analysis, membership function, segmentation, fuzzy sets of type-1, fuzzy sets of type-2.

Introduction. Fuzzy sets are currently used to solve a variety of problems in various areas of human activity, in particular, in image processing, in which inaccuracy and uncertainty are always present [1, 2].

One of the most challenging tasks in digital image processing is the segmentation process. Its implementation is complicated by the ambiguity associated with the image formation system, as well as the need to identify low-contrast objects or anomalies comparable to noise, about the nature, quantity, location and shape of which there is no a priori information [3].

Statement of the problem. The purpose of this article is to demonstrate the information capabilities of a new method for segmenting grayscale low-contrast images, which is based on the iterative application of fuzzy transformations of type-1 and type-2, which ensures an increase in its sensitivity and reliability.

Analysis. Traditionally, the transition to a fuzzy space (fuzzification) is carried out on the basis of the image initial brightness levels transformation into membership functions to fuzzy sets. Currently, effective methods for improving image quality based on transformations in fuzzy space have been developed [10].

In 1981, Bezdek proposed the fuzzy C-Means (FCM) clustering algorithm [4], which can be interpreted as a fuzzification process, since it generates a set of fuzzy membership functions (equal to the number of fuzzy clusters) that can be used to solve various problems,

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including image segmentation [5]. This algorithm provides automatic formation of a new multi-dimensional space of features describing objects of the subject area, allowing to take into account the uncertainty present in the initial data. The images always contain the ambiguity of grey, geometric fuzziness, and uncertainty of knowledge.

The concept of a type-2 fuzzy set was introduced by Zade [6], and Rhee and Hwang [5] presented a modification of the T2FCM fuzzy clustering algorithm using type-2 fuzziness to clarify the location of cluster centers (centroids). This approach is currently being actively developed and is often used to solve various problems [7, 8].

Disadvantages of the FCM algorithm include sensitivity to noise, uncertainty of initial parameters (fuzzification parameter and number of clusters), as well as ambiguity of the defuzzification stage.

Determining the number of fuzzy clusters in some cases is difficult due to the lack of a priori information about the subject area and causes the need to tune this value when solving specific problems. In [9], the algorithm is presented that allows you to automatically determine the optimal number of clusters, however, it is still necessary to set an initial value to start its work.

The matrix of centroids usage is necessary precisely when solving the task of fuzzy clustering, and segmentation is considered as a result of the visualization of its results. However, the matrix of centroids during segmentation is not considered critically important and is used primarily because it is required by the clustering algorithm.

Fuzzy transformations, which calculate the fuzzy membership function based on the original image, can also be used to improve image quality [10]. The application of such transformations, in principle, allows solving the task of segmentation, however, the iterative process of changing the membership function used by clustering algorithms, which allows you to control the detailing during segmentation, is not assumed.

The main part. The segmentation algorithm proposed in this paper operates with fuzzy membership functions of type-1 (MFT1) and type-2 (MFT2) and is iterative, which allows you to control the degree of its detail. However, this algorithm, unlike the FCM method and its modifications, does not use the matrix of centroids in principle, which simplifies the computational process. The stopping criteria are the specified error during training (it describes the change of fuzzy membership functions at different iterations), as well as the maximum number of iterations.

MFT1 is initially calculated on the basis of input data, and is not formed randomly, as in the basic FCM algorithm. The calculation of MFT2 is carried out on the basis of the difference of the "upper" u_h and "lower" u_l MFT1 (Fig. 1), which allow to fully describe the blur of the MFT1 (FOU – the footprint of uncertainty).

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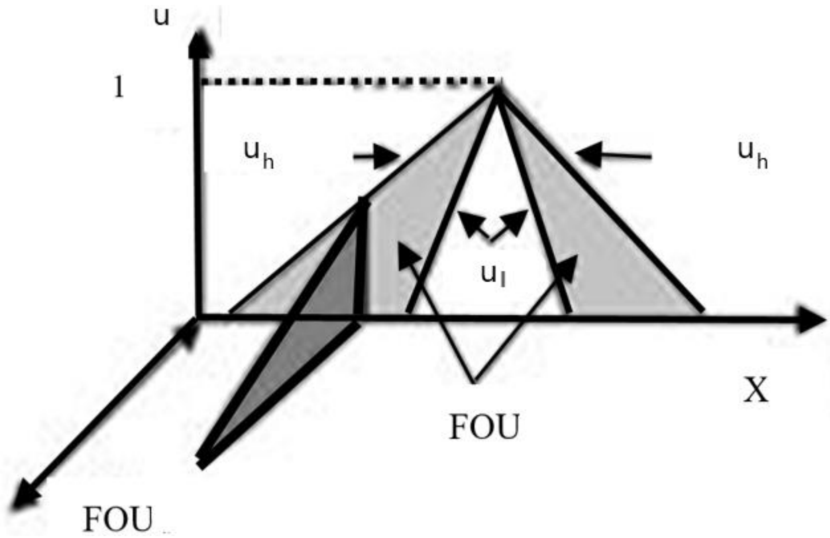

Figure 1 – Fuzzy sets of type_2: the boundaries of uncertainty

The algorithm of the method proposed in this paper contains the following steps:

1. Scaling the input halftone image to the range $[0,1]$.

2. Calculating the initial value of a MFT1 matrix u^0 (its dimension is $x_{\max} \times y_{\max}$ the same as for the input image) based on the scaled image using the following formulas:

$$u^0_{x,y} = \left| \left(I_{x,y}\right)^{1-\mathrm{sgn}\left(I_{x,y}-0.5\right)} \cdot \left(\frac{I_{x,y}}{I_{x,y}+C_1}\right)^{1+\mathrm{sgn}\left(I_{x,y}-\bar{I}\right)\cdot\frac{I_{x,y}}{I_{x,y}+C_1}} \right|, \tag{1}$$

$$C_1 = C_u + 0.6 - \bar{I}, \tag{2}$$

where $\bar{I}$ is the average of the input scaled image I, C_u is the coefficient, which is set on the basis of experimental researches, depends on the type of image being processed and significantly affects the segmentation results. The minimum recommended value of this coefficient is 0.02. The maximum depends on the images being processed. During the experiments, the maximum verified values of this coefficient were 120-130.

3. Calculating the current MFT2 matrix (a^t), the dimension of which is the same as that of the original image, is based on the difference of the "upper" u^t_h and "lower" u^t_l membership functions of the current iteration according to the following formulas:

$$\left(u^t_{h1}\right)_{x,y} = \left(\left(u^t\right)_{x,y}\right)^{1-\left(\left(u^t\right)_{x,y}\right)^{1+\left(\left(u^t\right)_{x,y}\right)^{1-\left(u^t\right)_{x,y}+\overline{\left(u^t\right)}^{1}-0.5}}}, \tag{3}$$

$$\left(u^t_{l1}\right)_{x,y} = \left(\left(u^t\right)_{x,y}\right)^{1+\left(\left(u^t\right)_{x,y}\right)^{1-\left(\left(u^t\right)_{x,y}\right)^{1-\left(u^t\right)_{x,y}-\overline{\left(u^t\right)}^{1}+0.5}}}, \tag{4}$$

$$\left(u^t_{h2}\right)_{x,y} = \left(\left(u^t\right)_{x,y}\right)^{K+0.75+\overline{\left(u^t\right)}^{1}/2}, \tag{5}$$

$$\left(u_{l2}^{t}\right)_{x,y} = \left(\left(u^{t}\right)_{x,y}\right)^{K+1.25+\left(\overline{u^{t}}\right)^{1}/2}, \quad (6)$$

$$\left(\overline{u^{t}}\right)^{1} = \left(\overline{u^{t}}\right)^{1-\max\left(\overline{u^{t}},1-\overline{u^{t}}\right)}, \quad (7)$$

$$\left(u_{h}^{t}\right)_{x,y} = \left(\left(u_{h1}^{t}\right)_{x,y} + \left(u_{h2}^{t}\right)_{x,y}\right)/2, \quad (8)$$

$$\left(u_{l}^{t}\right)_{x,y} = \left(\left(u_{l1}^{t}\right)_{x,y} + \left(u_{l2}^{t}\right)_{x,y}\right)/2, \quad (9)$$

where $\overline{u^{t}}$ is the average of the current matrix MFT1 u^{t} (on the 1st iteration the matrix u^{0} is used, and on the subsequent iterations matrix u^{t-1} is used, which is obtained at the end of the previous iteration), and K is the coefficient, the values of which should be selected in the range $[0,0.2]$, which affects the results of segmentation. It has been experimentally determined that it is most often recommended to select a value from 0.07 to 0.08.

4. Starting from the 2nd iteration of training:

4.1. The value Δ^{t} is calculated by the formula:

$$\Delta^{t} = \sum_{x=1}^{x_{\max}} \sum_{y=1}^{y_{\max}} \left| a_{x,y}^{t} - a_{x,y}^{t-1} \right|, \quad (10)$$

where a^{t} and a^{t-1} are MFT2 matrices of current and previous iterations, accordingly.

4.2. If the condition is met:

$$\Delta^{t} \geq \Delta^{t-1}, \quad (11)$$

where Δ^{t-1} is the value calculated by formula (10) at the previous iteration, initially this value is set to a very large number, unattainable in practice, then instead of the current values of the matrices a^{t}, u_{l}^{t} and u_{h}^{t} the values (a^{t-1}, u_{l}^{t-1} and u_{h}^{t-1}, accordingly) that are remembered at the end of the previous iteration are written, after which the learning process stops (go to step 7). This step prevents the overtraining effect from occurring.

4.3. If the condition is met:

$$\Delta^{t} < \varepsilon, \quad (12)$$

where ε is the specified learning accuracy, then the learning process also stops (go to step 7).

5. If the condition is met

$$t < t_{\max}, \quad (13)$$

where $t_{\max}$ is the maximum number of iterations, then the matrix value u^{t+1} is calculated, which will be used in the next iteration when calculating the a^{t} matrix. Matrix u^{t+1} is obtained by the formulas (1) and (2), where instead of the original image a matrix u^{t} of the current iteration is used, and instead of $\bar{I}$ value $\overline{u^{t}}$ is used.

6. If condition (13) is met, then the next learning iteration starts (go to step 3).

7. Values of matrices a^{t}, u_{l}^{t} and u_{h}^{t} are scaled to the range $[0,1]$.

8. Matrix I^{w} is calculated by the formulas:

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$$I_{x,y}^{w} = \left(u_{h}^{t}\right)_{x,y}^{1-\frac{a_{x,y}^{t}}{a_{x,y}^{t}+d_1}} - \left(u_{l}^{t}\right)_{x,y}^{1-\frac{a_{x,y}^{t}}{a_{x,y}^{t}+d_1}}, \quad (14)$$

$$d_1 = 2 + \overline{u_l^t}, \quad (15)$$

where $\overline{u_l^t}$ is average of u_l^t matrix. The obtained matrix I^w is also scaled to the range $[0,1]$ and is treated as a grayscale image.

9. The output image I^{out} is formed based on the weighted sum according to the formulas:

$$I_{x,y}^{out} = I_{x,y}^{h} \cdot C_{out} + I_{x,y}^{a} \cdot \left(1 - C_{out}\right), \quad (16)$$

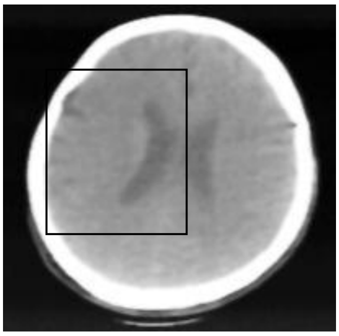
$$C_{out} = \left(\overline{I^w} + \overline{u_l^t}\right)/2, \quad (17)$$

where I^h and I^a are the grayscale images, obtained after applying the histogram equalization and adaptive histogram equalization methods (with a uniform transformation function) to the image I^w, accordingly, and $\overline{I^w}$ is the average of the image I^w.

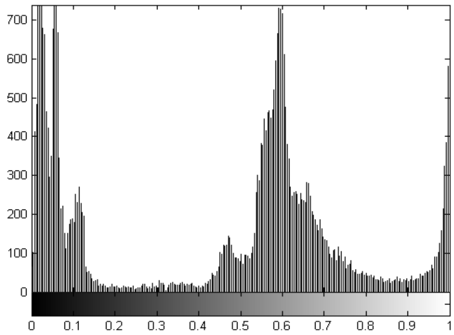
The experimental results were obtained on the example of processing various medical images, an example of which are the images shown in Fig. 2a, 3a (Fig. 2b and 3b show histograms of these images). Fig. 2a shows a tomogram of the brain, performed for the purpose of diagnosing the presence of a hematoma, as well as determining the area of its influence in case of detection (the rectangle indicates the area of interest). Fig. 3a shows an X-ray image of the cervical spine.

The following parameters were used for segmentation based on the FCM algorithm: $c = 6$, $m = 2$, $\varepsilon = 10^{-5}$, and the maximum number of iterations is 100. The results were visualized based on the maximum of the membership function.

The following control parameters were used when using the proposed method: $C_u = 0.026$, $K = 0.071$, $\varepsilon = 0.035$, the maximum number of iterations is 12 (during the experiments the number of training iterations practically did not exceed 3-4). Visualization of the original image was also carried out after scaling it to the range $[0,1]$ based on the formula (16), when $C_{out} = \overline{I}$.

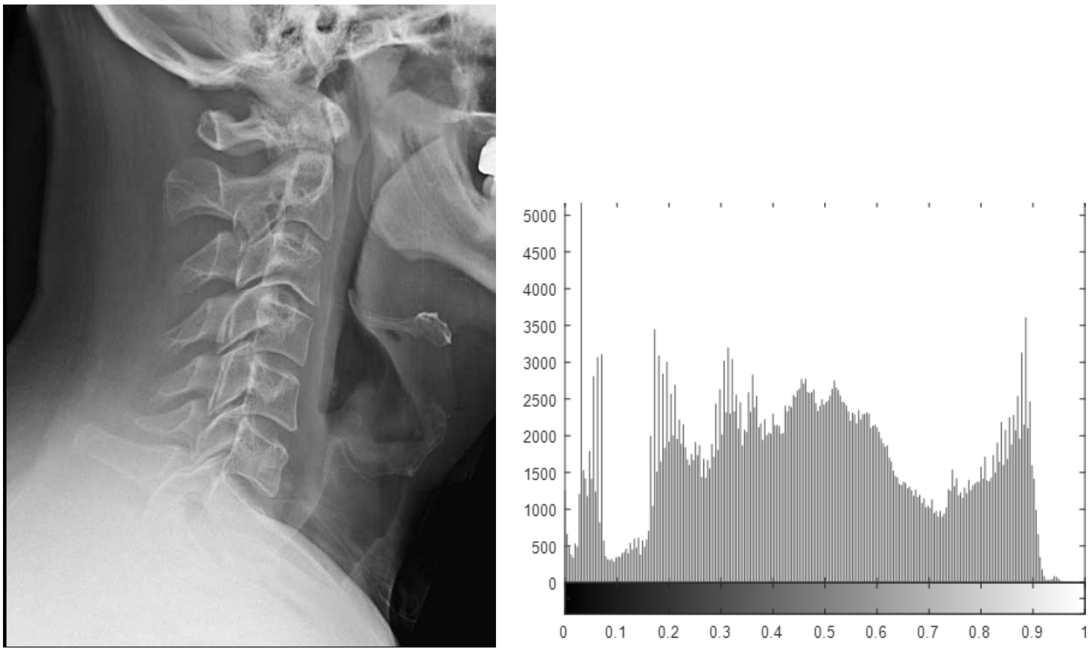


a



b

Figure 2 – X-ray tomogram of the brain: a – original grayscale image (204x201); b – its histogram

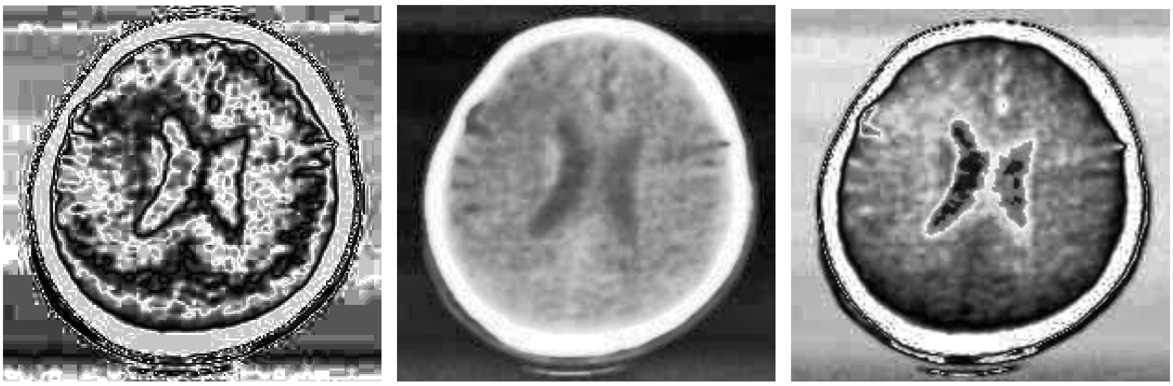


a b

Figure 3 – X-ray image: a – original grayscale image (744x570); b – its histogram

Segmentation of the brain tomogram shown in Fig. 1a based on the FCM algorithm (Fig. 4a) does not allow for a clear identification of the hematoma, and also leads to some excessive detailing: identification of image details that are insignificant for analysis, possibly artifacts. Visualization based on formula (16) of the original image does not allow for a clear identification of the hematoma's influence area (Fig. 4b). At the same time, segmentation based on the proposed algorithm allows for a clear identification of both the hematoma itself and its influence area (Fig. 4c).

Segmentation of the X-ray image shown in Fig. 3a by the proposed method also allows us to clearly highlight the structure of the cervical spine and part of the skull (Fig. 5b), which is poorly distinguishable in the original image. To a lesser extent, the highlighting of the structure of the cervical spine and part of the skull is provided by visualization of the original image based on formula (16), shown in Fig. 5a.



a b c

Figure 4 – Segmentation of the brain tomogram (Fig. 2 a): a – FCM; b – visualization of the original image according to formula (16); c – the proposed method

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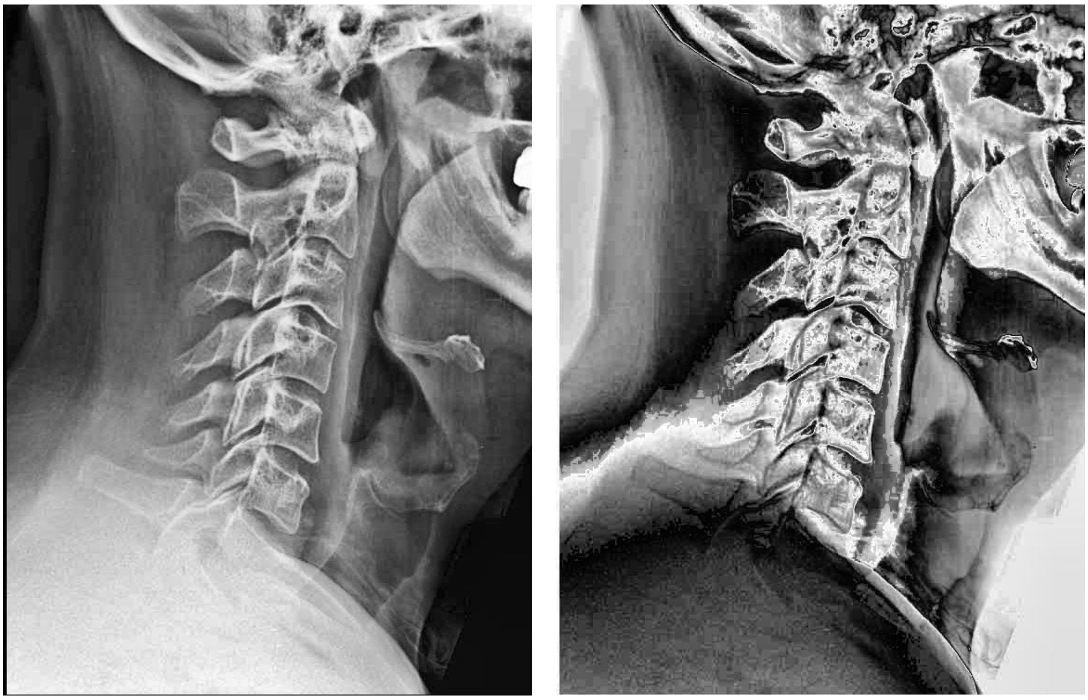

a b

Figure 5 – Segmentation of an X-ray image (Fig. 3a): a – visualization of the original image according to formula (16); b – the proposed method

Conclusions:

– the usage of the proposed method allows us to provide the level of detail necessary for visual analysis, more clearly identify the boundaries of interest and at the same time reduce the appearance of artifacts;

– the proposed algorithm is simpler than FCM and has a small number of control parameters;

– the level of detail is significantly affected by the parameter C_u, which is tuned to process the selected type of images;

– a promising direction for further research is to find ways to automate the tuning of the parameter C_u.

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Сегментація напівтонових слабкоконтрастних зображень на основі застосування нечітких перетворень типу-2

В роботі запропоновано алгоритм сегментації напівтонових зображень на основі ітеративного застосування нечітких перетворень типу-1 та типу-2, що забезпечує необхідну деталізацію результуючих зображень для візуального аналізу, запобігаючи при цьому передеталізації, має невелику кількість керуючих параметрів, та, на відміну від алгоритмів нечіткої кластеризації типу FCM, не використовує матрицю центроїдів, що спрощує розрахунки. Наведено експериментальні результати на прикладі сегментації запропонованим алгоритмом реальних напівтонових медичних зображень.
Ключові слова: слабкоконтрастні зображення, нечіткі методи, візуальний аналіз, функція приналежності, сегментація, нечіткі множини типу-1, нечіткі множини типу-2.

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