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SEGMENTATION OF LOW CONTRAST IMAGES ON THE BASIS OF THE TRANSFORMATION OF FUZZY MEMBERSHIP FUNCTIONS

Annotation. We studied the possibilities of the information segmentation of low-contrast image, which enhances its sensitivity and accuracy. The essence of his, lies in the fact that the accessory functions, obtained in the process of fuzzy clustering in each iteration, the procedure of conversion on the basis of fuzzy logic. Results of experimental verification with the help of real X-ray image are presented.

Key words: digital low-contrast image, the membership function, segmentation, fuzzy logic.

Introduction. Due to the complexity and ambiguity of the possible solutions of problems in the analysis of low contrast images due to the presence of these kinds of uncertainty as the ambiguity of gray, geometric vagueness, lack of knowledge about the availability and characteristics of objects of interest, as well as the system of their formation, are widely used methods of computational intelligence, in particular , fuzzy logic [1]. At the same time, in a variety of practical problems, such as medicine, geology, ecology, etc. require the identification of areas initially visually indistinguishable (objects of interest) and their boundaries. Such anomalies are often a small area, which can be mistaken for noise or image defect, and the parameters of objects of interest may be slightly different from each other and from a common background, have an unknown shape and fuzzy border.

A key issue for them is the formation of a new detection feature space on the basis of the analysis of the original contrast of its elements. Selection of different types of transformations of the original image and processing methods, leads to different results. For images with low contrast it is further necessary to carry out its pre-amplification.

The modern approach based on neuro-fuzzy technology has advantages over deterministic models [1, 2]. In [3] the method of analysis of information capabilities of low-contrast image, based on the method of fuzzy clustering, which is aimed at improving the reliability and accuracy of the segmentation in order to improve the possibilities of their perception of the human visual system.

The purpose of this work is to demonstration of information capabilities of the method of segmentation of low-contrast image, which is due to the transformation at each iteration step of fuzzy membership functions obtained in the process of fuzzy clustering, enhances its sensitivity.

The presentation of methods. For segmentation of low-contrast images in the work used a modified method dFCM (basic method has been considered in [3]), the algorithm which includes the following steps:

1. Initialization of the initial number of clusters c and centers v^0 of clusters of fuzzy values of the matrix; exponential weight fuzzy clustering m.
2. Calculation of the current membership functions u^t by the formula:

$$u_{k,i}^{t} = \sum_{L=1}^{c}\left[\frac{D_{i,k}}{D_{i,L}}\right]^{\frac{-2}{m-1}} \begin{pmatrix} \forall k \in \{1,\ldots,c\}, \\ \forall i \in \{1,\ldots,n\} \end{pmatrix}, \qquad (1)$$

where n - the number of the original data X. Matrix of distances D calculated based on fuzzy cluster centers of the previous iteration v^{t-1} by the formula:

$$D_{i,k} = \sqrt{\left(X_i - v_k^{t-1}\right)^T \left(X_i - v_k^{t-1}\right)}, \left(\forall i \in \{1,\ldots,n\}, \forall k \in \{1,\ldots,c\}\right). \qquad (2)$$

3. Dynamic transformation of the membership function:

3.1. membership functions of all fuzzy clusters as a whole or to each fuzzy cluster interpreted as the picture. Thus, before performing the dynamic transformation of the membership function or obtain a grayscale image dimension $[c \cdot n]$, or c-dimensional image dimension $[dy \cdot dx \cdot c]$, where dy and dx – the number of pixels horizontally and vertically, respectively, in the original image;

3.2. calculation of the index fuzziness $V_{fz}^{'}$ by the formula [1]:

$$V_{fz}^{'} = \left(\sum_{k=1}^{c}\sum_{i=1}^{n}\left(u_{k,i}^{t}\right)^2\right)/n; \qquad (3)$$

3.3. Contrast enhancement followed by scaling on the interval [0, 1] to the generated image;

3.4. calculation of the index fuzziness $V_{fz}^{''}$ by the formula (3), but using treated accessory functions.

3.5. if the condition $V'_{fz} > V''_{fz}$ is true, then merge accessories fuzzy matrix functions before and after ($\left(u''\right)^t$)the implementation of paragraph 3.3 by the formula:

$$u_{k,i}^t = u_{k,i}^t \cdot (0.5 + d_v) + \left(u''\right)_{k,i}^t \cdot (0.5 - d_v), \left(\forall k \in \{1,...,c\}, \forall i \in \{1,...,n\}\right), \quad (4)$$

where $d_v = 200 \cdot \left(V'_{fz} - V''_{fz}\right)^2$;

3.6. scaling the resulting membership functions to satisfy, it was made of the condition:

$$\sum_{k=1}^{c} u_{k,i} = 1, \left(\forall i \in \{1,...,n\}\right). \quad (5)$$

4. The calculation of the matrix of fuzzy cluster centers for the current iteration of the formula:

$$v_{k,j}^t = \left(\sum_{i=1}^{n} \left(u_{k,i}^t\right)^m \cdot X_{i,j} \right) / \sum_{i=1}^{n} \left(u_{k,i}^t\right)^m, \left(\forall k \in \{1,...,c\}, \forall j \in \{1,...,q\}\right), \quad (6)$$

where q − quantityof the informative features of each vector of source data.

5. Вычисление значения Δ_v^t как среднего по матрице расстояний между центрами нечетких кластеров 5. The calculation Δ_v^t of the average values of both the matrix of distances between the price-ters fuzzy clusters v^t, v^{t-1}, and criterias V_{xb}^t and V_{fz}^t (according to the formula (3)), which are indicators of Ksiye-Biyeni and the vagueness of the current iteration (decrease first and increase the second is characterized by improving the quality of fuzzy grouping), respectively, as follows [1]:

$$V_{xb}^t = \left(\sum_{k=1}^{c} \sum_{i=1}^{n} \left(u_{k,i}^t\right)^m \cdot \sum_{j=1}^{q} \left(X_{i,j} - v_{k,j}^t\right)^2 \right) / \left(n \cdot \left(d_{\min}^e\right)^2 \right), \quad (7)$$

where $d_{\min}^e$ − the minimum Euclidean distance between the centers of fuzzy clusters.

6. If $C_{fz}^t \ge C_{fz}^{\max}$, at that $C_{fz}^t = V_{fz}^t / V_{xb}^t$, where $C_{fz}^{\max}$ − maximum of coefficients C_{fz}^t derived in the learning process, the following values are stored: $\Delta_v^{\max} = \Delta_v^t$, $C_{fz}^{\max} = C_{fz}^t$, $u^{\max} = u^t$ и $v^{\max} = v^t$.

7. Unless the condition: $\Delta_v^t < \varepsilon$ or ($\left|V_{xb}^t - V_{xb}^{t-1}\right| < \varepsilon$ и $\left|V_{fz}^t - V_{fz}^{t-1}\right| < \varepsilon$), (8)

where V_{xb}^{t-1} и V_{fz}^{t-1} - indicators of Ksiye-Biyeni and fuzziness previous iteration, respectively, then the transition to step 2.

8. If $C_{fz}^{t} < C_{fz}^{\max}$ and ($\Delta_v^t > \Delta_v^{\max}$ or ($\Delta_v^t < \Delta_v^{\max}$ and $p_{\Delta_v} > p_c$)), the coefficients p_{Δ_v} and p_c is given by:

$$p_c = \frac{\left| C_{fz}^t - C_{fz}^{\max} \right|}{\max(C_{fz}^t, C_{fz}^{\max})} \cdot \frac{1}{C_{fz}^{\max} - C_{fz}^{\min}}, \tag{9}$$

$$p_{\Delta_v} = \frac{\left| \Delta_v^t - \Delta_v^{\max} \right|}{\max(\Delta_v^t, \Delta_v^{\max})} \cdot \frac{1}{\left(\Delta_v^{\max}\right)' - \Delta_v^{\min}}, \tag{10}$$

where $C_{fz}^{\min}$ и $\Delta_v^{\min}$ – minimum the parameter values C_{fz}^t and Δ_v^t, respectively, $\left(\Delta_v^{\max}\right)'$ – the maximum value of the criterion Δ_v^t, then return to the saved values of matrices of fuzzy membership functions $u^{\max}$ and fuzzy cluster centers $v^{\max}$, which are the result of learning.

With the implementation of paragraph 3.3 of the above algorithm for contrast enhancement in this study applied a method based on the use of probabilistic brightness characteristics [4], which assumes the implementation of conversion of each channel of the original image by the following rules:

$$\text{if } I_{\min}^1 \le I_{x,y}^1 < \beta_1 \text{, then } \mu_{x,y} = 2\left(\frac{I_{x,y}^1 - \overline{I^1}}{\overline{I^1} - I_{\min}^1} \right)^2; \tag{11}$$

$$\text{if } \beta_1 \le I_{x,y}^1 < \overline{I^1} \text{, then } \mu_{x,y} = 1 - 2\left(\frac{I_{x,y}^1 - \overline{I^1}}{\overline{I^1} - I_{\min}^1} \right)^2; \tag{12}$$

$$\text{if } \overline{I^1} \le I_{x,y}^1 < \beta_2 \text{, then } \mu_{x,y} = 1 - 2\left(\frac{I_{x,y}^1 - \overline{I^1}}{I_{\max}^1 - \overline{I^1}} \right)^2; \tag{13}$$

$$\text{if } \beta_2 \le I_{x,y}^1 < I_{\max}^1 \text{, then } \mu_{x,y} = 2\left(\frac{I_{x,y}^1 - \overline{I^1}}{I_{\max}^1 - \overline{I^1}} \right)^2, \tag{14}$$

where $\overline{I^1}$ – the average value of the luminance of the selected color channel of the input image; $\beta_1 = \dfrac{I^1_{\min} + \overline{I^1}}{2}$; $\beta_2 = \dfrac{I^1_{\max} + \overline{I^1}}{2}$; $\mu_{x,y}$ – the value of fuzzy membership function for pixel with coordinates x, y of the input image, $I^1_{\min}$ and $I^1_{\max}$ - the minimum and maximum brightness values for the selected color channel of the input image, respectively. Thereafter, the output image is formed as follows:

$$I^2_{x,y} = I^1_{x,y}\left(\mu_{x,y}\right)^2 . \qquad (15)$$

Experimental results. Presented modified algorithm has been applied in the processing of a variety of low-contrast grayscale medical images, examples of which are the pictures shown in fig. 1 - 2.

In fig. 1 an original low contrast a grayscale medical image (brain tomography) is presented. The purpose of diagnosis is to determine the influence of the hematoma. A histogram of the original image (fig. 1 b) shows that the image includes the entire range of brightness levels. However, the diagnosis of hematoma on the original pictures is difficult because of its location on a low-contrast image area (fragment obve-duced rectangle), and the area of its influence generally visually indistinguishable. Thus, it is a low-contrast image. The introduction of a radiopaque material (fig. 1), though allowing more clearly highlight the hematoma, but did not reveal the area of its influence.

Fig. 2 and which (fig. 2 b) shows a mammogram, the histogram, this picture should be attributed to the high-contrast image, however, fragment isolated rectangle is low contrast.

The following values of the control parameters were chosen in the experiments: $c = 6$, $m = 2$, $\varepsilon = 10^{-5}$. Visualization of fuzzy clustering results was performed by applying the method of comparison with the original data [3].

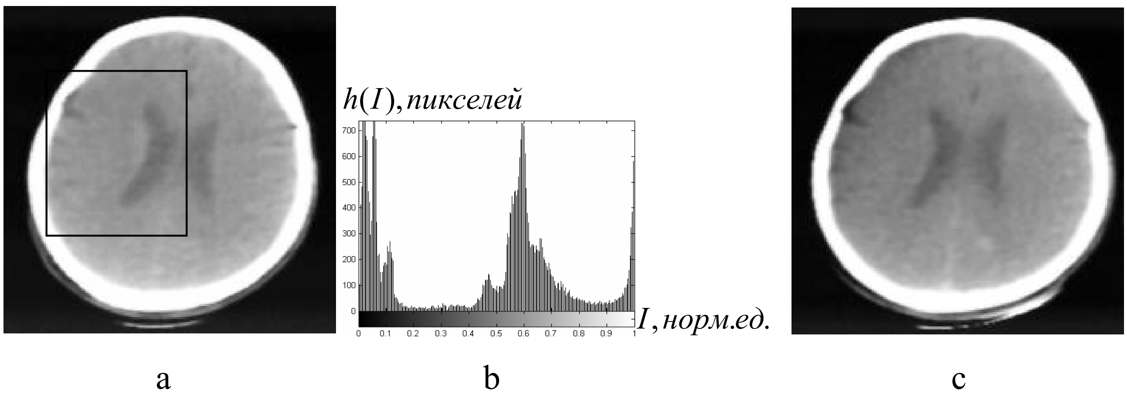
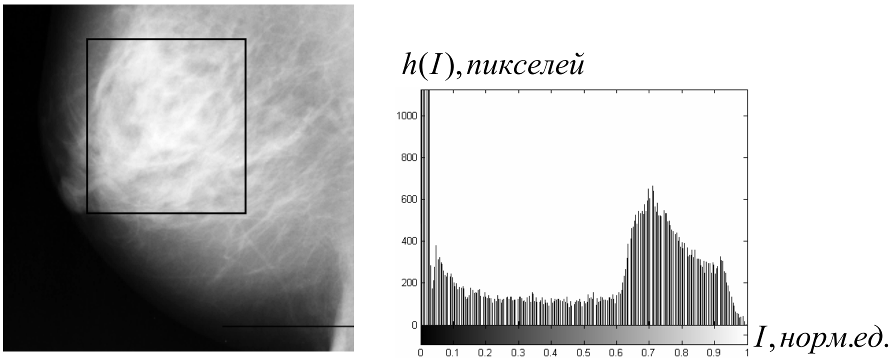


Figure - 1. X-ray tomography of the brain: a – the original grayscale image (204x201); b – histogram; c – the introduction of a radiopaque substance

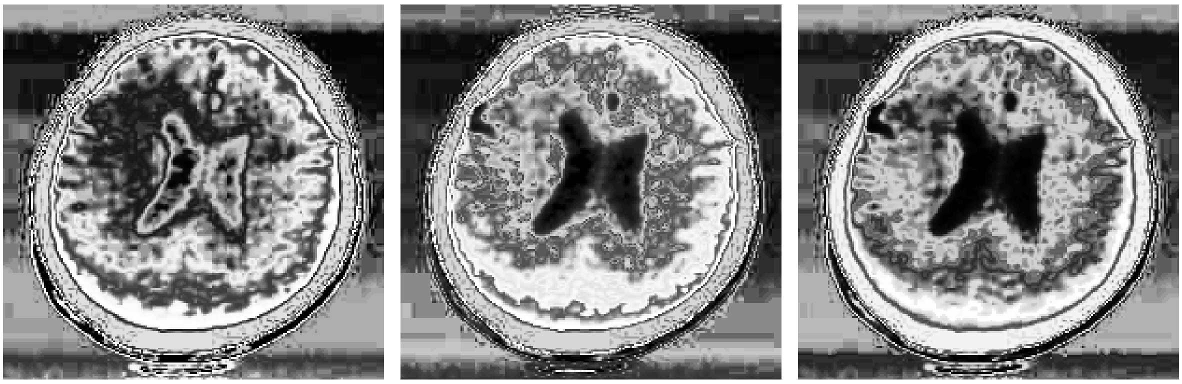


a b

Figure - 2. Mammogram: a– the original image (256x256);

b – histogram

Fig. 3 shows the segmentation of a tomogram (fig. 1 a) modified by dFCM. The absence of dynamic compression membership functions (fig. 3a) allowed to allocate only bruises. Failure to comply with paragraph 3.5 of the proposed method though and allows for detection of the hematoma influence, but does not provide a clear separation of its borders (fig. 3 b). At the same time, the performance of the dynamic transformation of the membership function in its entirety (fig. 3) made it possible to achieve the desired clarity in the allocation of boundaries of the area of influence of the hematoma.



a b c

Figure – 3. Segmentation of the image (fig. 1 a): a - without the dynamic transformation of the membership function, b - without performing p. 3.5;. b - with the implementation of the dynamic transformation of the membership function (3.1 -. 3.6)

Implementation of the proposed segmentation method mammograms (fig. 2a), the results of which are shown in fig. 4 shows that the use of a dynamic conversion membership function (without performing step 3.5) and may result in loss of detail in the region of interest (fig. 4. 2). However, the use of the dynamic transformation of the membership function in its entirety (fig. 4) to successfully cope with the elimination of the described disadvantage. It should, however, be noted that (4 in fig.) has not led to a

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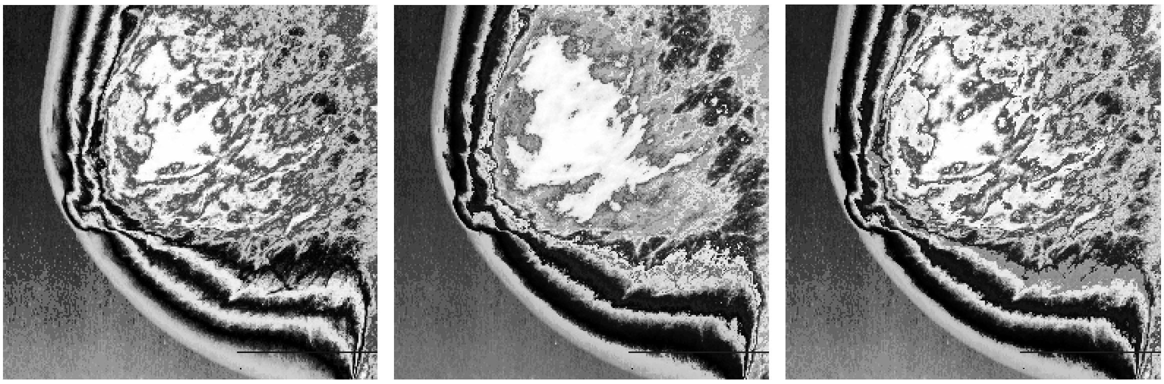
significant increase in the level of detail. It did not result in significant increase the level of detail of the region of interest compared without segmentation step 3 as a whole (fig. 4 a).

Conclusions. Based on the analysis of the experimental results can be Sde following conclusions:

– segmentation of low-contrast images of the proposed modified method allows dFCM when the dynamic transformation of the membership functions to achieve a higher degree of detail compared to the baseline algorithm;

– implementation of step 3.5 of the proposed method is an important step in the "stabilization" of the segmentation result with "failure" triggered method of increasing the contrast on some iterations.



a b c

Figure - 4. Segmentation of the image (fig. 2 a.): a - without the dynamic transformation of the membership function, b - without performing step 3.5; c - with the implementation of the dynamic transformation of the membership function (3.1 -. 3.6)

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