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Edge detection in MRI brain tumor images based on fuzzy C-means clustering

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Abstract

Nowadays, medical image processing is the most challenging and emerging field. Edge detection of MRI images is one of the most important stage in this field. The paper describes the proposed strategy to detect the edges of brain tumor from patient’s MRI scan images of the brain. At the first stage, this method includes some noise removal functions improving features that provides better characteristics of medical images for reliable diagnosis using Balance Contrast Enhancement Technique (BCET). The result of second stage is subjected to image segmentation using Fuzzy c-Means (FCM) clustering method. Finally, Canny edge detection method is applied to detect the fine edges. During the experimental study, we used images containing brain tumors that were characterized by different location, type of pathology, shape, size and density, as well as the size of the area of the affected tissue near the tumor space. Detection and extraction of tumor from MRI scan images of the brain is done using MATLAB software. The obtained results demonstrate some resistivity to a noise. Also, the accuracy of segmentation, in some cases of tumor pathology, was increased up to 10-15% regarding the expert estimates.

Keywords: Edge detection; median filter; fuzzy C means; Balance Contrast Enhancement Technique (BCET); Canny operator; medical imaging

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1. Introduction

Image processing techniques play an important role in the diagnostics and detection of diseases and monitoring the patients having these diseases. Edge detection is a fundamental tool in image processing, particularly in the areas of feature detection and feature extraction, which aim at identifying points in a digital image at which the image has discontinuities [1]. Already there is a lot of work which has been done in brain tumor detection. For the detection of tumor CT (computed tomography) or MRI (magnetic resonance imaging) images are uses. Corresponding medical equipment of these types brings a noticeable fraction of noise on the obtained images. Therefore, noise suppression is a necessary step to improve the accuracy of the analysis.

The existing methods of tumor detection and evaluation are divided into region-based and contour-based methods. Region-based methods [2-5] seek out clusters of pixels that share some measure of similarity. These methods reduce operator interaction by automating some aspects of applying the low-level operations, such as threshold selection, histogram analysis, classification, etc. In general, these methods take advantage of only local information for each pixel and do not include shape and boundary information. Contour-based methods [6-8] rely on the evolution of a curve, based on internal and external forces, such as image gradient, to delineate the boundary of brain structure or pathology. Many researchers use a wide range of techniques based on segmentation to solve the problem of localizing and analyzing the characteristics of a brain tumor. Priya and Verma [9] conducted medical image segmentation based on morphological operators along with threshold selection. Jain et al also used morphological operations along with threshold and watershed segmentation [10]. Also, Fuzzy C-Means (FCM) clustering method is often used for image segmentation [6-7]. Hemang J. Shah [11] proposed a hybrid approach, which is a combination of the watershed method and the Canny edge detection method to detect the tumor boundaries in an MRI image for different cases of brain tumor. And there are exists methods utilizing shearlet transform. One of them, during medical images processing, uses color coding for contour representation [12]. This methodology allows to analyze many parameters, including the formation of contour representation with color mapping of brain tumor according to stated settings (setting depend on the image). However, in most cases for an inexperienced user an inaccurate setting may not yield the correct results. Clear allocation of the contour of the tumor is a key moment in the problem under investigation since it determines the size of the surgical intervention and is essential in analyzing the tissue state near the tumor space to diagnose the development of an unfavorable process.

This article tries to solve the problem of how to make clearer the brain tumor contour with a minimal number of configurable parameters dependable on input image. Thus, we propose a set of computational procedures for image preparation for further analysis by medical specialists. In this set, two main components can be distinguished: improvement of image quality and segmentation of objects of interest (brain tumors) with the formation of an edge map. At the end a data analysis, calculation of parameters depending on the diagnostic task is conducted.

2. Proposed methodology

The quality of images obtained from medical devices can influence the result of processing (analysis) when solving diagnostic medical problems. In most cases, obtained images (or an image sets) have noticeable noise caused by technological features of devices operation. Considering this, authors suggest the following procedure to process the medical images (Fig. 1). On prestep the obtained images are converted to grayscale format. Then three main computational steps are performed:

1. Image enhancement
2. Edge map generation
3. Data analysis

During the image enhancement step, noise reduction (using one of the filters) and contrast enhancement is conducted. To improve the contrast for highlighting the area of interest we proposed to use Balance Contrast Enhancement Technique (BCET).

After image enhancement, it is suggested to use preliminary segmentation of the medical image to determine the boundaries of the area of interest most accurately. To perform the segmentation, the Fuzzy C-Means (FCM) clustering method was chosen. The final step in the formation of the edge map using Canny edge detector. The generated edge maps can be used for further analysis depending on the needs of medical specialists. The edge map allows to calculate the basic geometric characteristics (shape, area, spatial sizes, etc.) of objects of interest.

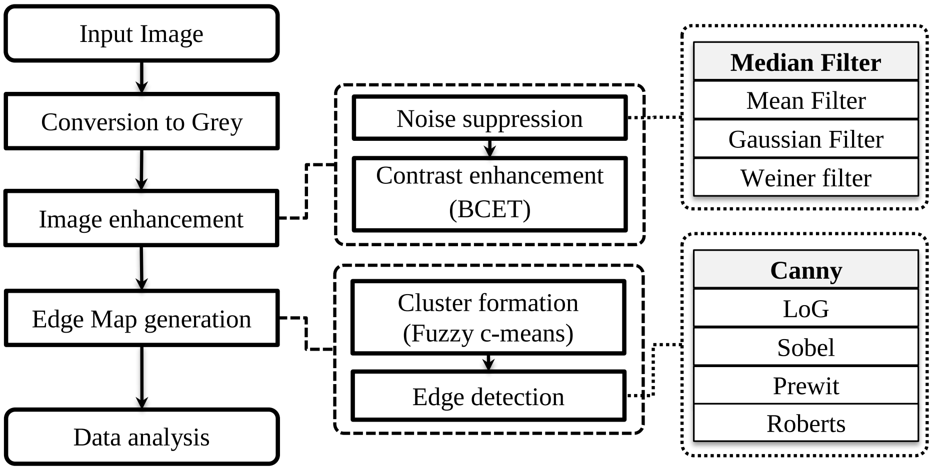

Fig. 1. The proposed algorithmic scheme for processing and analyzing the medical images

At the same time, for an area with an estimated content of the object of interest, an additional processing can be carried out, considering the factors of required analysis. Depending on the medical problem, color coding can be applied both within the area of interest and its surroundings for analyzing the state of tissues, etc. Color coding allows visualizing the fine features of the tissue structure near the tumor, which is necessary for subsequent procedures of a diagnostic nature and comparison with existing reference data.

2.1. Image enhancement

Various filters are used for image preprocessing. The primary purpose of these filters is noise reduction, but a filter can also be used to emphasize certain features of an image or remove other features. The most commonly encountered problems in medical imaging are Salt and Pepper, Speckle, Gaussian and Poisson noise. In various sources related to the medical image processing, Gauss filter, mean filter, median filter and their modifications are selected for noise suppression. Median filter is quite popular because, for certain types of random noise, it provides excellent noise suppression capabilities, with considerably less blurring than the linear smoothing filters of a similar size (mean or Gaussian). Taking this into account, median filter was selected as the main filter for noise suppression.

Median filter replaces the value of the pixel intensity by the median of the intensity levels in the adjacent pixels. Mathematically, the median filter can be described by equation (1) where I_{new}, I_{old} are the new and old values of the image pixels intensity, K is the kernel window with the dimensions $K_{Hs}\times K_{Ws}$ centered at pixel (x, y).

$$I_{new}(y,x) = \underset{(kx,ky)\in K_{xy}}{\mathrm{med}} \{I_{old}(kx,ky)\} \quad (1)$$

The original value of the pixel is included in the computation of the median. In this regard, it is particularly useful in removing speckle and salt and pepper noise.

Typically, during medical image processing, the contrast enhancement is required for the area of interest. For example, Contrast Limited Adaptive Histogram Equalization (CLAHE) allows to improve features and gain better characteristics of medical images for a right diagnosis [13]. Another example is LIP, PLIP and GLIP algorithms used to enhance an medical image and to improve visual quality of digital medical images. Conventional linear image enhancement methods often suffer from problems such as over-enhancement and noise sensitivity [14].

Unsharp masking is another interesting approach for image enhancement. It aims to enhance the edges and details, but usage of a high-pass filter also makes the method extremely sensitive to noise [13].

In proposed methodology we use Balance Contrast Enhancement Technique (BCET). The contrast of the image can be stretched or compressed without changing the histogram pattern of the input image (I_{Old}). The solution is based on the parabolic function obtained from the input image. The general form of the parabolic function is defined as:

$$I_{New} = a \cdot (I_{old} - b)^2 + c \tag{2}$$

Coefficients *a*, *b* and *c* are derived from the input, minimum value of the output image (I_{New}), maximum value of the output image, and mean value of the output image:

$$b = \frac{h^2 \cdot (E - L) - s \cdot (H - L) + l^2 \cdot (H - E)}{2 \cdot \left[h \cdot (E - L) - e \cdot (H - L) + l \cdot (H - E) \right]} \tag{3}$$

$$a = \frac{H - L}{(h - l)(h + l - 2b)} \tag{4}$$

$$c = L - a(l - b)^2 \tag{5}$$

$$s = \frac{1}{N} \sum_{i=1}^{N} I_{Old}^2(i) \tag{6}$$

where *l* and *h* are the minimum and the maximum values of the input image respectively, *e* is the mean value of the input image, *L* and *H* are the minimum and maximum value of the output image, *s* denotes the mean square sum of the input image.

2.2. Edge detection

The edge map can be generated with different algorithms, such as Roberts, Prewitt, Sobel and more complex ones, for example, LoG and Canny. However, the accuracy of their work will depend on the original image. The image after image enhancement has many levels of intensity gradation, which, during edge detection, can lead to the formation of false edge fragments and so on. Taking this into account, a preliminary segmentation with Fuzzy c-means clustering method were used.

Fuzzy C-Means clustering performs clustering by iteratively searching for a set of fuzzy clusters and the associated cluster centers that represent the structure of the data as best as possible. It allows to split an existing set of points of power *n* by a given number of fuzzy sets. A special feature of the method is the use of a fuzzy membership matrix $\mathbf{W}=\{w_{ik}\}$, which elements determine the degree of membership of the *k*-th element of the initial set of vectors to the *i*-th cluster. Given a number of clusters *c*, FCM clustering divides the data $\mathbf{X} = \{\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_n\}$ into *c* fuzzy clusters with the centers of the clusters $\mathbf{V} = (\mathbf{v}_1, \mathbf{v}_2, \ldots, \mathbf{v}_c)$ by minimizing objective function:

$$F(W,V) = \sum_{i=1}^{c} \sum_{k=1}^{n} (w_{ik})^m \cdot \left\| \mathbf{x}_k - \mathbf{v}_i \right\|^2, \quad w_{ik} \in [0,1], \quad i = \overline{1, c}, \quad k = \overline{1, n}, \quad 1 \le m < \infty, \tag{7}$$

where *m* is the fuzziness index, w_{ik} is the degree of membership of $\mathbf{x}_k$ in the *i*-th cluster, $\mathbf{v}_i$ is the center of the *i*-th cluster, and $\|\mathbf{x}_k - \mathbf{v}_i\|^2$ represents the distance between the data $\mathbf{x}_k$ and the cluster center $\mathbf{v}_i$.

$$w_{ik} = \left(\sum_{j=1}^{c} \left(\frac{\|\mathbf{x}_k - \mathbf{v}_i\|}{\|\mathbf{x}_k - \mathbf{v}_j\|} \right)^{2/(m-1)} \right)^{-1}, \qquad \sum_{i=1}^{c} w_{ik} = 1, \tag{8}$$

$$\mathbf{v}_i = \frac{\sum_{k=1}^{n} (w_{ik})^m \cdot \mathbf{x}_k}{\sum_{k=1}^{n} (w_{ik})^m} \tag{9}$$

In each iteration of the FCM clustering algorithm, matrix W is computed using Eq. 8 and the associated cluster centers are computed as Eq. 9. This is followed by computing the square error in Eq. 7. The algorithm stops when either the error is below a certain tolerance value or its improvement over the previous iteration is below a certain threshold. The number m governs the influence of membership grades in the performance index. The partition becomes fuzzier with increasing m, and if $m \to \infty$ all objects will belong to all clusters with the same degree. The number m also allows, when calculating the coordinates of cluster centers, to strengthen the influence of objects with large values of degrees of membership and to reduce the influence of objects with small values of degrees of membership.

After splitting the image into a series of homogeneous classes using the FCM clustering algorithm, the Canny edge detector is applied. It is based on the gradient value of a pixel and is used to determine fine edge, while the image includes homogeneous regions. The steps of this method can be described as follows. At the first step the Gaussian filter is used to smooth out the original images. Next, the magnitude and direction of the gradient are determined for each pixel in the image. The next step is a selection the boundary pixels (edge pixels). A pixel is considered as boundary pixel if the magnitude of the gradient of this pixel is greater than that of two neighbors in the direction of the gradient.

The example of a step-by-step formation of an edge map according to the proposed methodology is shown in Fig. 2.

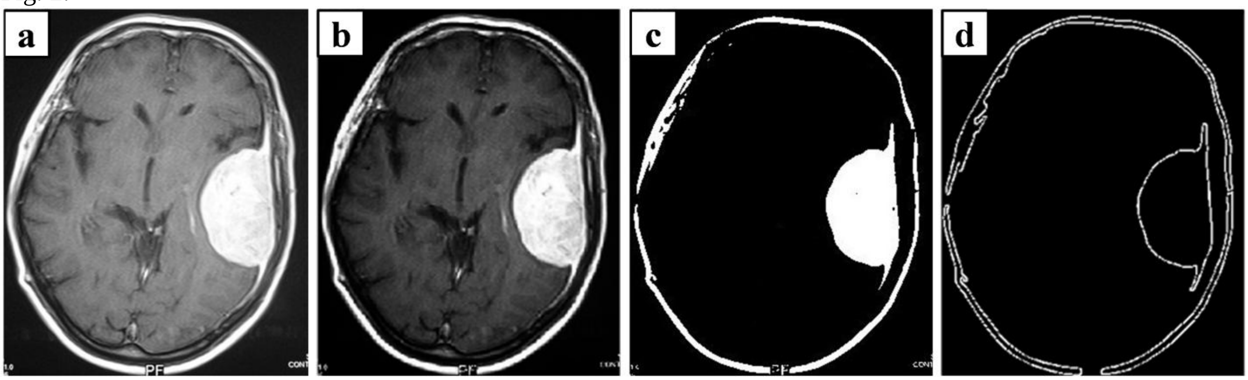

Fig. 2. Example of the proposed method work: a) original image, b) enhanced image, c) result after FCM clustering, d) final edge map

3. Experimental research

For the experimental research 30 images were selected. Examples are shown in Fig. 3. Medical images contain tumors that are characterized by different locations and different types of pathologies, shape, size and density, as well as the size of the area of the affected tissue near the tumor space.

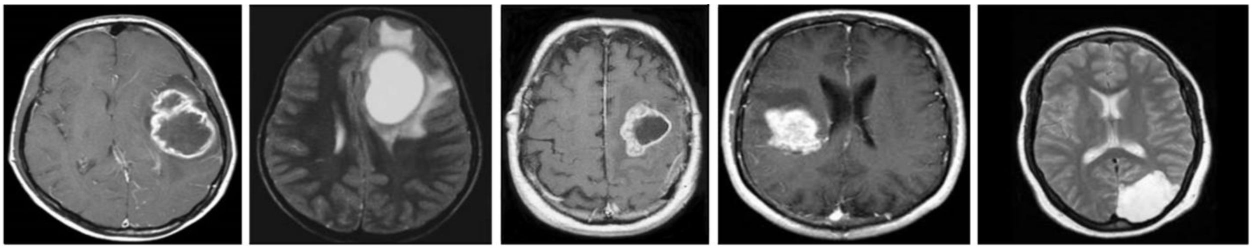

Fig. 3. Experimental data set images

To show that the proposed methodology has good edge detection capability and is resistant to average level of noise, the following studies were carried out. The first study implies comparing the proposed method with classical approaches to edge detection based on simple gradient operators such as Roberts, Prewitt, Sobel and complex methods LoG and Canny. For the comparison, the images with the least pronounced noise influence were selected. All evaluation parameters during study were calculated with help of reference images created by the medical expert. Fig. 4 shows an example of reference edge maps drawn by an expert.

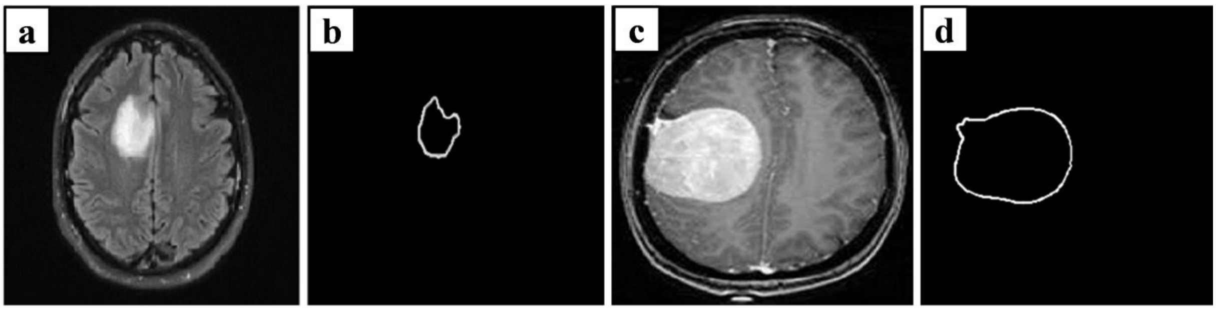

Fig. 4. Examples of external contour of brain tumor indicated by an expert: a) c) original images, b) d) contour of brain tumor

To evaluate the reliability and correctness of the brain tumor edge map obtained by proposed method the following parameters were used: percentage of pixels detected (P_{CD}), percentage of pixels not detected (P_{ND}), percentage of false alarm (P_{FA}), figure of merit (*FOM*), sensitivity and accuracy. These parameters are mostly depending on the value of *TP*, *TN*, *FP*, *FN* and RE_{Cnt}. True positive (*TP*), the number of pixels correctly identified as tumor boundary. True negative (*TN*), the number of pixels correctly detected as background. False positive (*FP*), the number of pixels falsely identified as tumor boundary. False negative (FN), the number of pixels falsely detected as background. Reference edge count (RE_{Cnt}) represents the number of edge pixels in reference map created by expert.

The percentage of pixels that were correctly detected is and is defined as:

$$P_{CD} = \frac{TP}{RE_{Cnt}} \tag{10}$$

The range of metric lies between 0 and 1. Maximum value is optimal. If value is 1, then it shows the perfect match between the images. Else if its value is 0, then there is no similarity between images.

The percentage of pixels that were not detected is P_{ND}. For this indicator, the minimum value (equal to 0) is optimal. The P_{ND} value is calculated according to the expression:

$$P_{ND} = \frac{FN}{RE_{Cnt}} \tag{11}$$

The percentage of pixels that were erroneously detected as edge pixels that is the percentage of false alarm is P_{FA} and is defined as:

$$P_{FA} = \frac{FP}{RE_{Cnt}} \tag{12}$$

The Figure of Merit (FOM) of Pratt is another useful measure for assessing the performance of edge detectors. This measure uses the distance between all pairs of points corresponding to quantify with precision, the difference between the contours. The FOM, which assesses the similarity between two contours, is defined as:

$$FOM = \frac{1}{\max(RE_{Cnt}, AE_{Cnt})} \cdot \sum_{i=1}^{AE_{Cnt}} \frac{1}{1+\alpha \cdot d_i^{\,2}} \tag{13}$$

where RE_{Cnt} and AE_{Cnt} are the number of ideal (reference) and actual edge point, d_i is the distance between an edge pixel and the nearest edge pixel of the reference, α is an empirical calibration constant (was used α =1/9, optimal value established by Pratt [15]).

The FOM reaches its maximum value one to similar images and dissimilarity gives minimal value. Sensitivity or true positive rate computes how much percentage of object pixels correctly detected as object pixel. The range of metrics lies between 0 to 1 and maximum value is optimal. The sensitivity can be described by equation:

$$Sensivity = \frac{TP}{TP+FN} \tag{14}$$

Accuracy is the proportion of true results. Accuracy gives percentage of how much object and background pixels exactly detected. The range of metrics lies in between 0 to 1. If accuracy value is 1, then the output is the same as input. The accuracy is defined as:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{15}$$

Table 1 demonstrates a comparison of several techniques for the formation of a contour representation (edge map) of the brain tumor for the model images shown in Fig. 3. The data is obtained for local area of interest. Examples of generated edge maps are shown in Fig. 5.

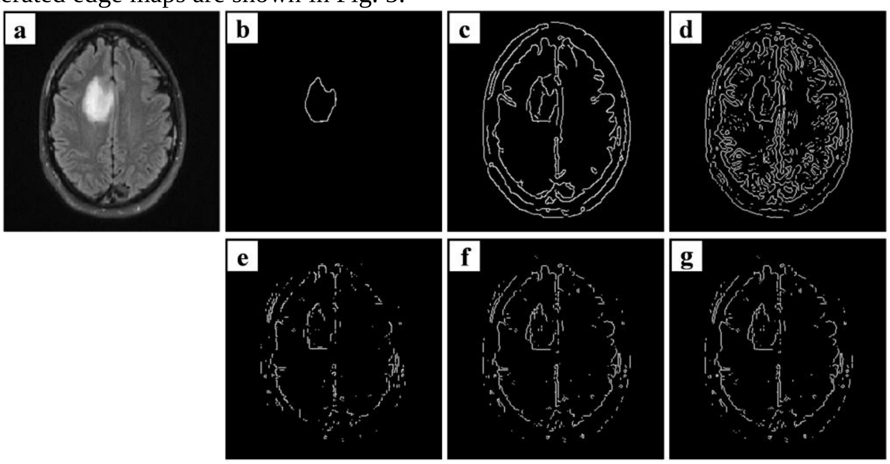

Fig. 5. Example of edge maps generation: a) original image, b) Proposed method, c) Canny, d) LoG, e) Roberts, f) Prewitt, g) Sobel

Table 1. Comparison of the edge maps generated by different edge detection methods for model images

Model Image	Method	P_{CD}	P_{ND}	P_{FA}	FOM	Sensitivity	Accuracy
Image 1	Proposed method	0.4935	0.1301	0,5065	0.9272	0.9735	0.9894
	Classic Canny	0.4652	0.3852	0.5348	0.3601	0.4230	0.9482
	Prewitt	0.3357	1.0425	0.6443	0.2907	0.4824	0.9473
	Roberts	0.2406	0.5792	0.7594	0.3224	0.5181	0.9373
	Sobel	0.3427	1.0132	0.6573	0.2903	0.5108	0.9541
	LoG	0.3903	0.8663	0.6026	0.1923	0.2096	0.9058
Image 2	Proposed method	0.5081	0.0932	0.4919	0.8896	0.8576	0.9934
	Classic Canny	0.4211	0.5021	0.5789	0.3347	0.4521	0.9592
	Prewitt	0.3703	0.4649	0.6297	0.4373	0.4285	0.9506
	Roberts	0.2516	0.4060	0.7484	0.4131	0.3825	0.9489
	Sobel	0.3764	0.4687	0.6236	0.4338	0.4246	0.9587
	LoG	0.2923	2.9092	0.7077	0.2418	0.1195	0.9053

The proposed method allows to obtain an edge map of the object of interest with more accuracy on average by 3-7%. Also, proposed method demonstrates a lower percentage of pixels that were erroneously detected as the edges of the brain tumor. Fig. 6 represents a graph with comparison of the average values of the FOM, Sensitivity and Accuracy characteristics for a test database of 30 images.

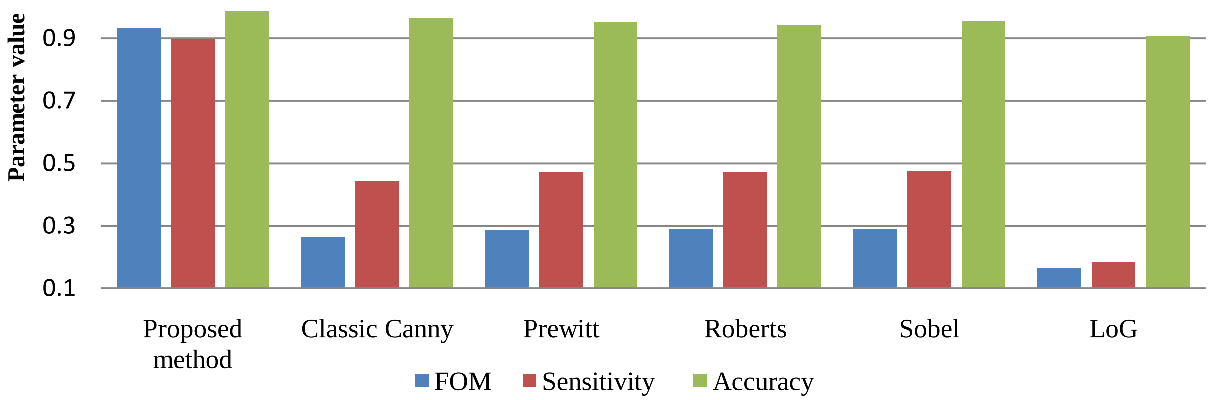

Fig. 6. Comparison of edge map generation methods by key parameters

To assess the impact of noise on the obtained result, according to the proposed method, an additional study was carried out on model images (Fig. 4). To simulate the noise which may occur in the equipment, the following noise characteristics were used. In the total noise map the impulse noise part amounts to 30% while the additive noise part is 70%, with the value of the additive noise component being up to 15% of the dynamic range of the experimental data. The experimental study was carried out as follows. For the selected medical images, the noise with the distribution being 5, 10, 15, 20 and 30%, was added. After that, the proposed method was applied, and the parameters were calculated. For each noise level 30 evaluations were conducted. Fig. 7 represents summary data on the changes in the edge map characteristics obtained by proposed method depending on the noise level. Fig. 8 shows the average changes in the FOM, Sensitivity and Accuracy values obtained for 10 different images. As can be seen from figures the FOM and Accuracy values are almost do not change with increasing noise level. The change is less than one percent for a noise level lower than 25%. However, the sensitivity index shows a more marked decrease, while being within the acceptable range.

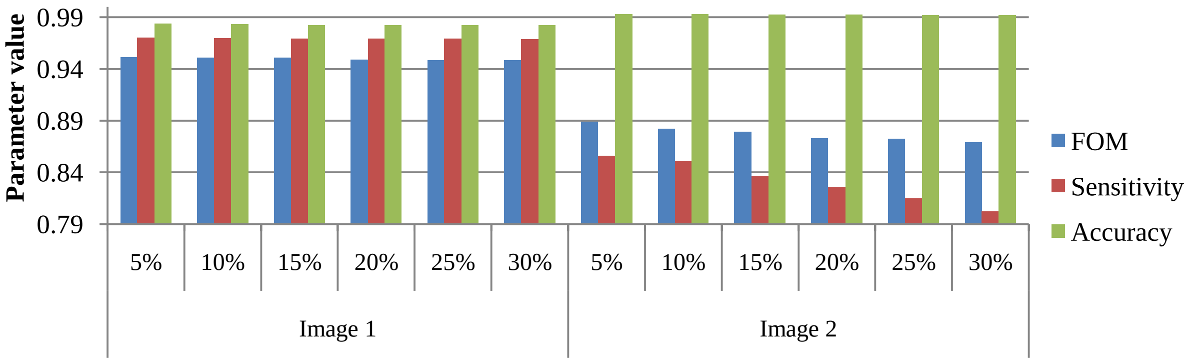

Fig. 7. Dependence of the parameters' values on the noise level for model images

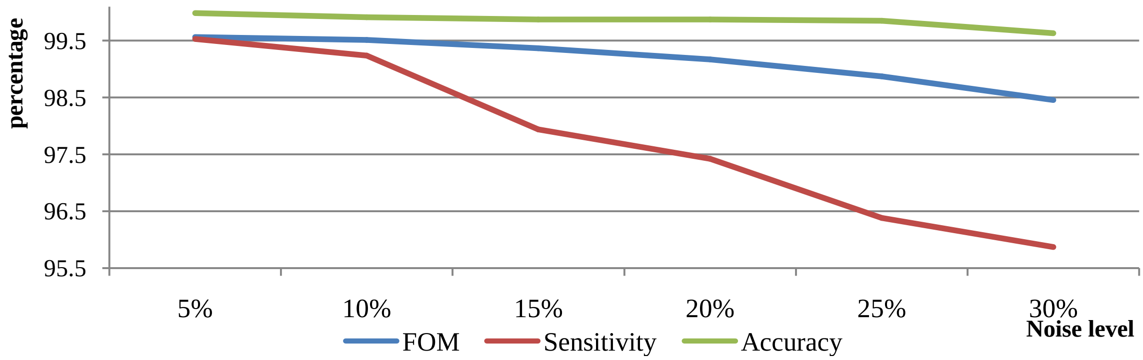

Fig. 8. Estimation of the decrease in the values of key parameters in relation to the noise level

4. Conclusion

MRI Brain's tumor edge detection in medical images helps doctors during diagnosis. This is not an easy task because the source images often have low quality because of limitations of the equipment. Therefore, edge detection technique must be high. The paper presents a MRI Brain's tumor edge detection based on Fuzzy C-Means in medical image processing system. The input image is denoised with median filter and enhanced by BCET. Then, image is segmented by FCM clustering method and Canny edge detector is applied to construct the edge map of brain tumor. The proposed method performs better because Canny method is applied for ideal input images which have improved quality and segmented into homogeneous regions thanks to the BCET and FCM. As a result, the proposed method gives a good result which presents high image quality for the analysis by medical specialist. Evaluation of the edge maps by medical expert demonstrated that in some cases of tumor pathology the accuracy of solving the problems of geometric analysis and segmentation is better by 10-15% relative to the corresponding expert estimates. The conducted experimental research demonstrated the stability of edge map generated by the proposed method to the noise's influence.

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