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DEVISING A METHODOLOGY FOR X-RAY IMAGE CONTRAST ENHANCEMENT BY COMBINING CLAHE AND GAMMA CORRECTION

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Increasing image contrast is very important for the visual analysis of X-ray images. To improve the contrast of medical images, various contrast enhancement methods are used, such as histogram equalization and histogram modifications, gamma correction, etc. The paper explores adaptive methods for enhancing the contrast of digital X-ray images. Research was carried out on 1000 images from the open Kaggle database. Combinations of sequential application of several methods for enhancing image contrast were evaluated. Experiments using gamma image correction allowed us to select ranges of input and output parameters of the brightness conversion function. To obtain a better result, before performing gamma correction, it is proposed to use the method of equalizing the histogram of an X-ray image. Possibilities of adaptive image histogram equalization are explored. The performed experiments allow us to propose an improved version of increasing the contrast of X-ray images. Combining the adaptive histogram equalization algorithm with contrast clipping has a visually noticeable effect of improving the contrast of X-ray images. Contrast improvement is supported by objective NIQE and BRISQUE quantifications that do not require reference images. A feature of this work is the use of objective non-reference assessments to determine the quality of images. The performed experiments indicate that the NIQE score correlates better with the visual assessment of image contrast changes. As a result of the experiments, recommendations were proposed for choosing the parameters of the gamma correction and adaptive histogram equalization methods, which make it possible to enhance the contrast without the intensification of noise in the image

Keywords: digital X-ray image, image quality evaluation, image enhancement, contrast enhancement

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1. Introduction

The idea of image enhancement techniques is to reveal details of objects that are hidden, or simply highlight certain features of the image. One example of improvement is to increase the contrast of an image by stretching its dynamic range of brightness values. The term "contrast" observed in digital images is described by the ratio of the brightness of the dark and light areas present in the image [1]. Image enhancement depends on its context. An enhancement method that works well in improving biomedical images may not be as effective in improving satellite images. Medical images play an important role in the diagnosis of diseases and monitoring the effect of selected treatment methods. Environmental noise, special conditions of patients when photographing, lighting conditions and technical limitations of imaging devices are among the reasons why images may have poor quality. In such cases, image enhancement techniques may be useful. They are used to repair damaged images, and an effective contrast enhancement method can improve the fine details of the image so that radiologists can properly monitor the patient's health. Therefore, the study of methods of contrast enhancement of medical images is relevant.

2. Literature review and problem statement

While getting acquainted with the experience of other researchers in this subject area, the methods considered in foreign literature were studied. The paper [2] discusses the increase in contrast based on the internal decomposition of the image, using the separated algorithm of Bregman and CLAHE (Contrast limited adaptive histogram equalization). The authors show the improvement of images by assessing the levels of illumination and reflection using the internal decomposition of the image. As a result, a good contrast improvement was obtained, but the proposed method is intended only for contrast enhancement and cannot be used for such methods as changing the surface texture, inserting objects, etc.

The paper [3] considers the optimized display of the perception tone to increase the contrast of images. The proposed method focuses on a person's visual attention by constructing a brightness histogram and performs contrast enhancement. The advantage of the method is that it improves performance without excessive contrast enhancement. To enhance the contrast with this method requires more time compared to the HE (Histogram equalization), CLAHE methods.

The authors of [4] propose an effective method for changing histograms and increasing the contrast of digital images. The paper presents an automatic conversion method that improves the brightness of darkened images using gamma correction and the probability distribution of brightness pixels. It is used to improve video data. The method proposed in the paper uses the differences between frames to reduce computational complexity. Experimental results have shown that the proposed method allows obtaining improved images of comparable or higher quality than those obtained using other methods.

In [5], the author proposed an algorithm for increasing contrast based on local histogram equalization. A feature of the algorithm is the determination of the number of subhistograms and the division of the histogram based on saturation. The algorithm worked in three stages. Initially, the estimation of the number of clusters for image brightness levels is performed using histogram equalization. In the next step, the brightness levels of the image are grouped and finally include contrast enhancement for each individual cluster separately. The algorithm is compared with other methods based on the measurement of quality and quantity. The application of the method gives the natural appearance of the images and increased contrast. The disadvantages of the algorithm are the loss of detail at high levels of image brightness and the presence of noise in the output image.

In [6], the authors proposed a new method for improving medical images. First, the original medical image is decomposed into an NSCT region (nonsubsampled contourlet transform) with a low-frequency sub-band and several high-frequency sub-bands. Then a linear transformation was used for the brightness coefficients of the low-frequency sub-band. An adaptive threshold method is used for noise reduction of the coefficients of high-frequency sub-bands. Then all the sub-ranges were reconstructed into spatial regions using the reverse NSC transformation. Next, blurry masking is applied to increase the clarity of the details of the reconstructed image. The experimental results show that the proposed method is superior to other methods in such characteristics as image entropy and PSNR (peak signal-to-noise ratio).

The paper [7] discusses an approach optimized for social networks to combine images to increase contrast and maintain brightness. The social network optimization algorithm creates two high-quality images, one with better contrast, increased entropy, and the second image with an increased peak signal-to-noise ratio. Both images are combined to get an effective image later. Comparisons were carried out using HE, linear contrast stretching. The results show that the proposed method provides a better peak signal-to-noise ratio, preserves brightness, increases the contrast of any given image, which leads to a high-quality visual effect. However, the number of edge pixels of this technique is large, while the fitness value is smaller.

The paper [8] proposes a method of contrast enhancement in the wavelet domain based on entropy. Initially, it uses local entropy scaling in the wavelet domain to obtain the desired contrast. Mathematical methods were used, and then a method was developed to improve the color in the HSI color space (from the English hue, saturation, lightness (intensity)). The algorithm worked in two stages: modification of low frequencies in the wavelet region and scaling of the HSI color space by increasing the intensity component so that images in low light receive detailed color information without any subsequent processing. A feature of the algorithm is that it is used in the HSI color space and provides an increase in image contrast.

In [9], a combination of contrast limited adaptive histogram equalization and discrete wavelet transform to improve the image is proposed. The algorithm works in three stages. First, the original image is distributed over low-frequency and high-frequency components using a wavelet transform. The low-frequency coefficients are improved using the CLAHE method, while the high-frequency coefficients remain unchanged. With the reverse wavelet transform, the image is mounted successfully. The proposed method is applicable to improve local image details, preserves details well and suppresses noise. But the high-frequency component, which contains most of the noise in the original image, remains unchanged.

The authors of [10] propose high-speed quantile-based histogram equalization (HSQHE) to preserve the brightness and increase the contrast of the image. Contrast enhancement by this method is suitable for high-contrast digital images. Recursive segmentation of the histogram is not performed, so segmentation requires minimal time. Entropy indices are used to estimate the PSNR of contrast enhancement. AMBE (Absolute Mean Brightness Error) is used to evaluate brightness retention. HSQHE preserves the brightness of the image more accurately in a shorter period of time, but a high PSNR value is achieved only for certain images.

In [11], the authors propose a scheme for modifying the histogram with entropy maximization. The method of modifying the entropy maximization histogram divides the global equalization of the histogram into two stages: the stage of pixel populations merging (PPM), which is consistent with the entropy maximization rule, and the stage of gray levels distribution (GLD). The application of the method gives a good improvement, avoids increased noise and distortion in the image, but there is a problem of excessive contrast stretching.

Familiarization with the proposed methods confirms the need to use methods of nonlinear image brightness conversion to improve contrast, but their detailed study is required to obtain a more informative image after processing. The methods of contrast enhancement described above have their advantages and disadvantages. However, many researchers do not use quantitative estimates of the contrast changes in the transformed images.

3. The aim and objectives of the study

The aim of the study is to devise a methodology of contrast enhancement of X-ray medical images.

To achieve the aim, the following objectives were set:

– to analyze the main steps of the gamma correction and CLAHE for X-ray medical image processing;

– to develop a methodology for the use of adaptive contrast enhancement methods.

4. Materials and methods of research

The object of our research is the process of increasing the contrast of the X-ray image.

The main hypothesis of this study suggested that the combination of adaptive histogram equalization with gamma image correction makes it possible to significantly improve the contrast of X-ray images.

The following research methods were used in the course of the study: mathematical apparatus of matrix theory; methods of probability theory and mathematical statistics; methods of image processing theory; methods of system analysis; methods of mathematical modeling.

In the course of the study, the following limitations and assumptions were adopted:

– medical X-ray images are considered as images;

– medical images are digital;

– X-ray images from the Kaggle database were used [12];

– causes such as environmental noise, special conditions of patients when photographing, lighting conditions and technical limitations of imaging devices lead to poor quality of X-ray images;

– digital medical images allow us to apply approaches to image improvement based on direct conversion of image pixel values;

– when assessing the quality of an X-ray image, it is necessary to take into account that low-contrast X-ray images do not have standards for comparison;

– consistent application of several methods to improve the contrast of the image gives the best result.

Image enhancement methods involve performing such transformations on the original image that lead to a result more suitable for a specific application [13]. Visual assessment of image quality is an extremely subjective process, and automatic calculation of the quantitative value of such an assessment is a very difficult task. To choose one or another method to increase the contrast of a medical image, it is necessary to evaluate the result. Algorithms for objective quality assessment are divided into reference and non-reference. Different reference criteria use a comparative quality assessment when it is usually known what the reference image looks like and its characteristics are known [14]. When working with low-contrast medical images, there are no standards for comparison. Therefore, it is necessary to select those evaluation opportunities that do not require a reference image.

Image enhancement approaches are divided into two categories: spatial domain processing methods and frequency domain processing methods. The term spatial domain refers to the image plane as such, and this category combines approaches based on the direct transformation of image pixel values. Frequency methods assume image changes after the Fourier transform.

Let us consider some methods related to processing methods in the spatial domain. Spatial methods are described by the equation [13]:

$$g(x,y)=T\left[f(x,y)\right], \tag{1}$$

where f(x, y) is a function describing the original image, g(x, y) is the transformed image, T is an operator over f defined in some neighborhood of the pixel with coordinates (x, y). The neighborhood of a pixel is a square or rectangular area that is a subset of the image and centered relative to this pixel. The simplest version of the operator T occurs when the neighborhood consists of a single pixel, in which case the value of g is a function of f(x, y) and T is called a point-type transformation.

Gradation transformations are divided into the following groups: linear logarithmic and power transformations. Histogram equalization of a digital image is a transformation of the original image, in which the histogram of the transformed image has a more horizontal shape than the histogram of the original image.

To improve the image quality, it is necessary to increase parameters such as brightness range, contrast, sharpness, clarity. Together, these parameters can be improved by aligning the histogram of the image. Histogram equalization algorithms are widely used to improve the processed digital halftone image. In general, such algorithms are easy to implement, have a relatively low computational cost and at the same time show high efficiency. The essence of the work of such algorithms is to adjust the levels of the halftone image in accordance with the probability distribution function of this image (2) and, as a result, the dynamic range of the brightness distribution increases. This leads to improved visual effects, such as: brightness contrast, sharpness, clarity.

$$P(i)=\frac{n_i}{n},\quad i=0..255;$$

$$H(j)=255\cdot\sum\nolimits_0^j P(i), \tag{2}$$

where $P(i)$ is the probability of a pixel with brightness i, the normalized histogram function of the original image, j is the pixel coordinates of the processed image, $H(j)$ is the transformed image [13]. Histogram equalization algorithms are divided into the following two types: local (adaptive) histogram equalization and global histogram equalization. In the global method, one diagram is constructed and the histogram of the entire image is aligned. In the local method, a large number of histograms are constructed, where each histogram corresponds to only a part of the processed image. With this method, the local contrast of the image is improved, which makes it possible to obtain better processing results in general.

An improved version of the above algorithm is the adaptive histogram equalization algorithm with contrast restriction (contrast limited adaptive histogram equalization – CLAHE). The main feature of this algorithm is the limitation of the histogram range based on the analysis of pixel brightness values in the processed block (3) thereby the resulting image looks more natural and less noisy [15].

$$da = \frac{n_c}{n}, \tag{3}$$

where *da* is the increment factor of the histogram function value, n_c is the number of pixels exceeding the threshold value.

It is worth noting that the classic CLAHE algorithm uses bilinear interpolation to eliminate the boundaries between the processed blocks.

The *imadjust* function is a basic tool in the MATLAB package for converting the brightness of halftone images. All input parameters of the *imadjust* function are real numbers in the range from 0 to 1, i. e. the range of brightness values must be normalized.

The syntax of the function is defined as follows:

$$J = imadjust\begin{pmatrix} I,[low\_in, high\_in], \\ [low\_out, high\_out],\gamma \end{pmatrix}. \tag{4}$$

The *imadjust* function converts the intensity values of the halftone image *I* to new values and writes them as a matrix *J*. By default, *imadjust* discards 1 % of all lower and upper brightness values in image *I*, then applies linear contrast stretching.

The function *J=imadjust* (*I,* [*low_in, high_in*], [*low_out, high_out*]) converts the original brightness values of *I* to new values of *J* from the range [low_in, high_in] to the range [*low_out, high_out*]. The latter can be equal to [0, 1].

The function *J=imadjust*(*I,* [*low_in, high_in*],[*low_out, high_out*], γ) additionally performs gamma correction of the converted brightness values. By default, the parameter γ=1, which corresponds to an identical mapping [13].

Histogram equalization in MATLAB is implemented by the *histeq* function, which has the syntax:

$$(\;,\;), \tag{5}$$

where *I* is the input image, *n* is the number of intensity levels set for the output image *J*. If *n* is equal to the total number of possible levels of the input image, then *histeq* simply implements the conversion function. If this number is less than the total number of possible levels of the input image, then *histeq* will redistribute the levels so that they approximate the flat diagram. For the true implementation of this method, the maximum possible number of levels is used for *n*, i.e. 256. The CLAHE algorithm is implemented by the *adapthisteq* function, which has the following syntax:

$$J = adapthisteq(I, Name, Value). \tag{6}$$

The input parameters of *Name* can be:

– number of tiles – The number of rectangular context areas (tiles) into which *adapthisteq* divides the image specified as a 2-element vector of positive integers;

– contrast enhancement limit – Contrast enhancement limit set as a valid scalar in the range [0, 1];

– number of histogram bins used to build a contrast enhancing transformation – The number of histogram intervals used to build a contrast enhancing transformation (default is 256);

– desired histogram shape;

– distribution parameter.

CLAHE works with small areas of the image called tiles, not the entire image. *adapthisteq* calculates the contrast conversion function for each tile individually. The contrast of each tile is increased, so that the histogram of the output area approximately corresponds to the histogram set by the value "Distribution". Adjacent tiles are then combined using bilinear interpolation to eliminate artificially created boundaries. Contrast, especially in homogeneous areas, can be limited to avoid amplifying any noise that may be present in the image.

To perform experiments on the application of image brightness conversion methods, several dozen X-ray images from the Kaggle database were used [12]. The aim of the experiments is to find a method to increase the contrast of X-ray images of lungs for their more informative presentation. The essence of methods for improving the quality of medical images is as follows: apply mathematical methods to low-contrast images and improve the contrast of digital medical images to improve diagnostic accuracy.

5. Research results of contrast enhancement of X-ray medical images

5. 1. Gamma correction of X-ray images

A number of experiments have been carried out to apply the brightness conversion function of halftone images (4) to several X-ray images to select the most appropriate input parameters. The values for the input and output parameters were selected in 0.1 increments in the range from 0 to 1 [16]. Here, for each selected value [*low_in, high_in*], [*low_out, high_out*], the parameter γ was selected from the range [1, 44.5] in increments of 0.5. From all [*low_in, high_in*] [*low_out, high_out*], those with the best values of γ were selected, then they were compared with each other.

During the experiments, a number of brightness ranges of the original images were sorted out, for which attempts to increase the contrast of X-ray images gave a positive result both visually and in the form of quantitative estimates. To determine how much the contrast increased, the non-reference evaluation functions NIQE and BRISQUE, included in the basic image processing package of the MATLAB system, were used.

The evaluation functions NIQE (Naturalness Image Quality Evaluator) [17] and BRISQUE (Blind/Referenceless Image Spatial Quality Evaluator) [18] are used in cases where there is no image standard. The NIQE (A) function compares the image quality of A relative to an abstract model image based on images of natural scenes. The BRISQUE (A) function compares the quality of image A relative to another model image constructed from a series of images of natural scenes with certain distortions. The smaller the values of these functions, the higher the image quality. When selecting the necessary parameters with the selected values, you can visually display the result of the conversion and compare it with the original image (Fig. 1).

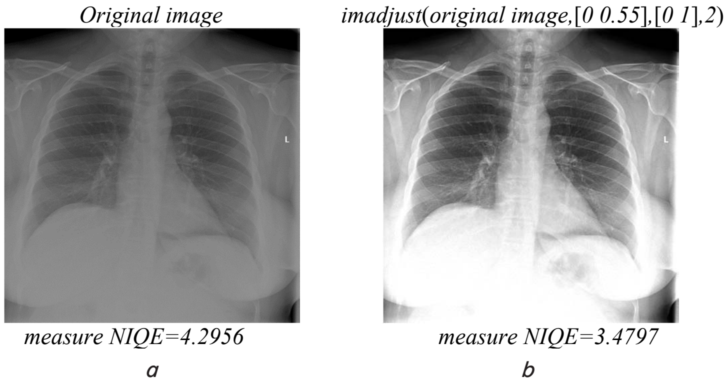


Fig. 1. Image comparison: *a* – the original image; *b* – transformation using the *imadjust* function

Fig. 1 shows the original image (*a*) and the result of applying the *imadjust* function with the parameters ([0, 0.55], [0, 1], 3). Here, the NIQE score of the original image is 4.2956, and for the transformed image, the score is 3.2738. It is possible to note a higher contrast of the transformed image, as evidenced by a lower NIQE quantification value than that of the original image.

When choosing the value of the parameter γ, in most cases of using the *imadjust* function, the conversion result did not give a visual improvement, which was confirmed by quantitative estimates. For example, Fig. 2 shows the results of converting the original 4.png image with different parameters.

5. 2. Combination of adaptive histogram equalization method with gamma image correction

The result of using the function *imadjust*(orig_image,[0 0.65],[0,1]) (Fig. 2, *b*) has estimates equal to NIQE=3.8334 and BRISQUE=12.1771, which decrease after applying gamma correction (Fig. 2, *c*) with the same parameters and γ=2, NIQE=3.5692 and BRISQUE=11.4306. There is a slight visual improvement. The equalization of the histogram of the original image (Fig. 2, *d*) visually improves it simultaneously with a decrease in the NIQE=4.2516 score, but the BRISQUE score increases. Applying the *imadjust* function to the result of histogram equalization with the same parameters without gamma correction (Fig. 2, *e*) shows a slight visual improvement, but the values of both ratings are increasing. Gamma correction applied to the aligned source image (Fig. 2, *f*) also does not visually improve it.

Applying the histogram equalization (5) of the original image before testing the *imadjust* function with the choice of the parameter γ gives the result of improved image contrast (Fig. 2, *d*). Therefore, it can be noted that before applying gamma correction, it is necessary to align the histogram of the original image. But the results of gamma correction after equalization do not give a noticeable improvement in the image. In the following experiment, methods were used to align the histogram of several images with a comparison of their results with the quality of the original image. For example, for the above 4.png image (*a*), the application of the *imadjust* function after histogram equalization (*b*) and after adaptive histogram equalization with contrast restriction (*c*) is shown in Fig. 3.

Fig. 3 shows that the application of the method of adaptive equalization of the image histogram with limited contrast before gamma correction (Fig. 3, *c*) in comparison with the equalization of the image histogram (Fig. 3, *b*) visually gives a better result. Here, the NIQE score for the original image is 4.2956, and for the transformed image after histogram equalization, the score is 3.926, whereas after adaptive equalization, the score is 3.4044. It is possible to note a higher contrast of the transformed image and a quantitative assessment of NIQE shows a lower value than that of the original image. The BRISQUE score shows an improvement in the result of adaptive histogram equalization, but its value is not less than the value of the original image score.

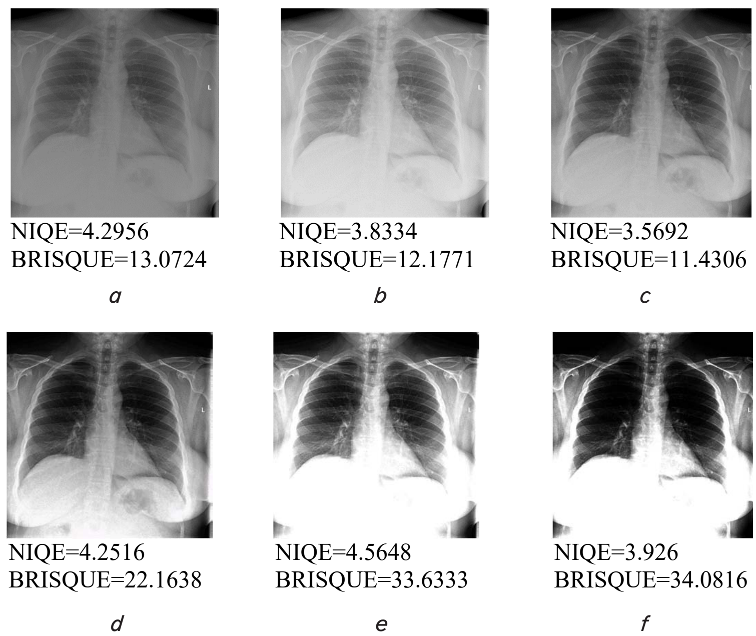


Fig. 2. Image conversion: *a* – the original image; *b* – brightness conversion with parameters [0, 0.65], [0, 1]; *c* – brightness gamma correction with parameters [0, 0.65], [0, 1], γ=2; *d* – histogram equalization of the original image; *e* – applying *imadjust* to the result of equalizing the histogram of the original image with parameters [0, 0.65], [0, 1]; *f* – applying gamma correction to the result of equalizing the histogram of the original image with parameters [0, 0.65], [0, 1], γ=2

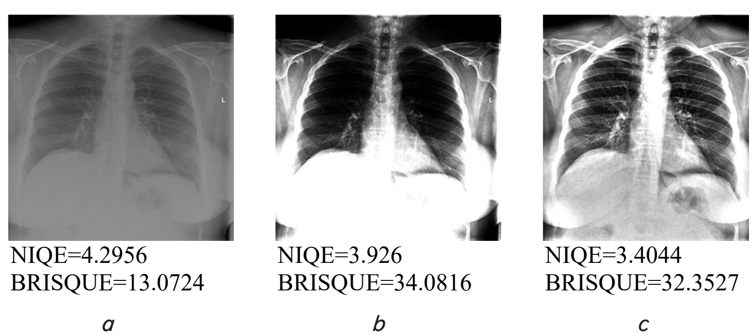


Fig. 3. Comparison of the results of histogram equalization methods, *a* – the original image; *b* – application of *imadjust* with parameters [0, 0.65], [0, 1], γ=2 to the result of HE; c – application of *imadjust* with parameters [0, 0.65], [0, 1], γ=2 to the result of CLAHE

Table 1 shows two quality ratings of 20 test images before and after applying the histogram equalization and CLAHE methods. In most cases, the results of using the CLAHE method demonstrate a visual increase in the contrast of images and a decrease in the values of estimates at the same time. In some cases, the estimates of the results of using adaptive equalization with contrast restriction do not decrease in comparison with the estimates of the original image. The best scores are highlighted in bold.

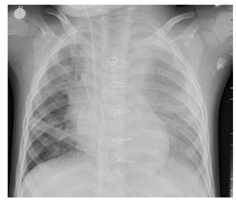
Table 1

Image estimates after applying histogram equalization methods

Image title	Original image		Result of histogram equalization		Result of CLAHE	
	NIQE	BRISQUE	NIQE	BRISQUE	NIQE	BRISQUE
1.png	4.0372	16.1975	**3.8041**	18.5971	**3.2715**	**10.6472**
2.png	4.2881	18.7059	**4.0796**	25.8175	**3.3852**	**6.6687**
3.png	4.1413	10.4101	4.8412	29.7437	**3.4034**	**8.2951**
4.png	4.2956	13.0724	**4.2516**	22.1638	**3.5460**	14.6105
5.png	4.3203	25.7744	**3.8508**	27.6071	**3.1356**	29.5149
6.png	4.8023	29.9513	5.4088	40.3179	**4.2207**	**28.3585**
7.png	4.1236	32.9393	**4.8747**	**37.4808**	**3.4908**	33.0683
8.png	4.9052	20.7902	5.2407	27.6747	**3.9651**	25.4163
9.png	4.2157	34.7177	4.9093	36.0444	**3.7676**	**30.8811**
10.png	3.9375	30.1194	5.1471	39.5292	**3.8944**	**14.6258**
11.png	3.5497	30.8850	4.3799	30.7679	**3.4329**	**10.2117**
12.png	4.4868	28.2587	**4.3719**	**27.5564**	**3.6503**	**19.0598**
13.png	3.4792	20.0601	4.3538	29.9863	**3.2307**	**3.1725**
14.png	4.0546	25.4383	4.8640	39.0374	**3.8017**	**9.9179**
15.png	3.9641	18.4571	**3.6307**	23.2339	**3.2276**	**10.7398**
16.png	4.3019	28.3591	6.3466	41.8677	**3.9429**	**14.8815**
17.png	3.6039	12.8875	**3.3539**	25.8919	**2.9714**	28.4774
18.png	4.6498	10.9344	**4.1434**	16.1989	**3.5850**	**8.1012**
19.png	3.8410	19.6463	**3.7533**	29.8566	**3.3647**	**16.8759**
20.png	4.4724	20.6639	**3.7059**	30.9653	**3.5707**	**12.4969**

In some cases, the objective estimates after the image transformation are not reduced, for example, the estimates for the image person3_bacteria_10.jpeg. A subjective assessment of the results of the transformation of this image, shown in Fig. 4, indicates the greatest contrast of the right image. This is the result of adaptive equalization of the image histogram with limited contrast. It should be noted that not in all cases objective assessments correlate with visual (subjective) assessment, but there are not many of them.

As a result of analyzing the data in Table 1, it was decided that in order to improve the results of image contrast enhancement, it is advisable to replace the histogram equalization method with adaptive histogram equalization with contrast restriction. In the following experiment, function (6) was used to increase the contrast of image I in grayscale by converting values using adaptive histogram equalization with contrast restriction. The effect of the Distribution and Multiplimit parameters on image improvement was investigated. The Distribution parameter takes the values 'uniform', 'rayleigh', 'exponential', these are the names of distributions that set the desired shape of the transformed image histogram. The choice of distribution can be associated with the type of input image. For example, underwater images seem more natural when using the 'rayleigh' distribution.

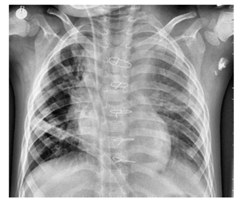


NIQE=2.8316
BRISQUE=21.7251

a

NIQE=2.914
BRISQUE=22.7425

b



NIQE=3.1578
BRISQUE=21.8798

c

Fig. 4. The results of the transformation: *a* – the original image; *b* – by the method of histogram equalization; *c* – the CLAHE method

The ClipLimit parameter locally changes the contrast ratio, which prevents oversaturation of the image brightness, especially in homogeneous areas. These areas are characterized by a high peak on the histogram of a particular image fragment due to the fact that many pixels fall into the same range of gray levels. Without this parameter, the adaptive histogram equalization method can give results that are in some cases worse than the original images. The default value of this parameter is 0.01.

The following experiment was performed for test X-ray images:

– to determine the optimal value of the 'clipLimit' parameter, its values were selected from the interval [0, 1] in increments of 0.01;

– objective NIQE and BRISQUE estimates were calculated for all original and transformed images;

– graphs of objective estimates were plotted for all transformed images;

– the minimum values of NIQE and BRISQUE ratings were determined.

Visually optimal images were selected that corresponded to the minimum objective estimates.

The graphs of objective estimates (Fig. 5) constructed for X-ray images showed that the range of values of the cliplimit parameter can be limited from [0, 1] to [0, 0.2], since subsequent values do not change the estimates. The minimum measures of NIQE and BRISQUE ratings allow you to select images with improved contrast. This choice corresponds to the statement that the lower the value of the non-reference estimate, the visually the image is more contrasting, i.e. its quality is better. This statement was confirmed during previous studies, when the minimum value of the NIQE score more often coincided with an improvement in visual perception of the image.

Fig. 6 shows a visual comparison of the original image (Fig. 6, *a*) with the transformed ones, where the CLAHE method is applied with the selected parameters and with the minimum NIQE score (Fig. 6, *b*) and the minimum BRISQUE score (Fig. 6, *c*). Here the value of the distribution parameter is 'rayleigh' and those transformed images for which non-reference scores had minimum values are selected. For example, for image 1.png, a transformed image was obtained that has a minimum NIQE score=2.9012 with cliplimit=0.12, it corresponds to the BRISQUE score value=15.314. For the same image with a minimum BRISQUE score of 9.1993 with the value of the parameter cliplimit=0.01, the NIQE score=3.2265 is determined. It can be noted that a decrease in the BRISQUE score in many cases does not correspond to a decrease in the value of the NIQE score, at which visual improvements in image contrast were observed.

The constructed graphs of objective estimates for the converted images of the original '1.png' by adaptive histogram equalization with contrast restriction are shown in Fig. 7. Here the distribution parameter takes the value 'exponential'; and the 'clipLimit' parameter gets values from the interval [0.02] with a step of 0.01.

Fig. 8 shows a visual comparison of the original image (Fig. 8, *a*) with the transformed ones, where the CLAHE method is applied with the selected parameters and with the minimum NIQE score (Fig. 8, *b*) and the minimum BRISQUE score (Fig. 8, *c*). Here the value of the distribution parameter is 'exponential' and those transformed images for which non-reference scores had minimum values are selected. For example, for image 1.png, a transformed image was obtained that has a minimum NIQE score=2.8036 with cliplimit=0.15, it corresponds to the BRISQUE score value=12.6992. For the same image with a minimum BRISQUE score of 6.9796 with the value of the parameter cliplimit=0.02, the NIQE score=3.0005 is determined. When comparing the objective estimates of the original image with the estimates of the transformed images, it can be noted that here visual improvements in image contrast are observed simultaneously with a decrease in both objective estimates.

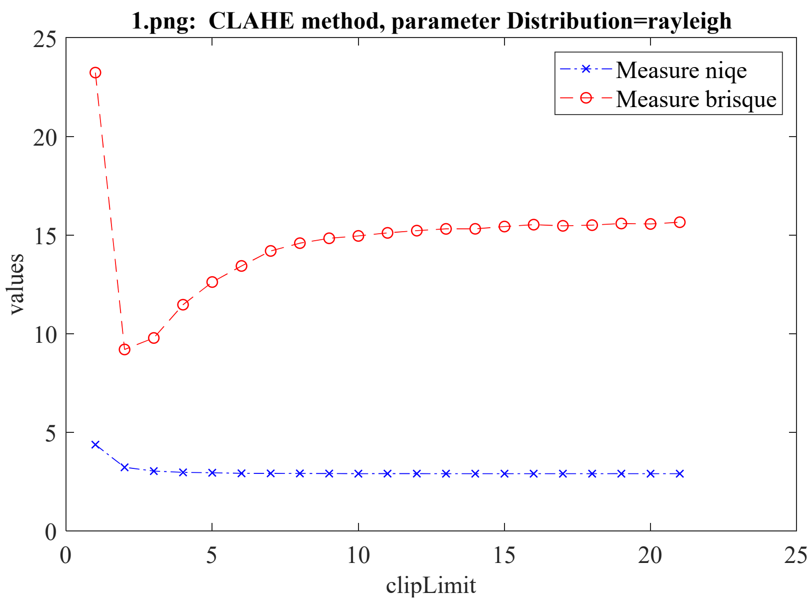
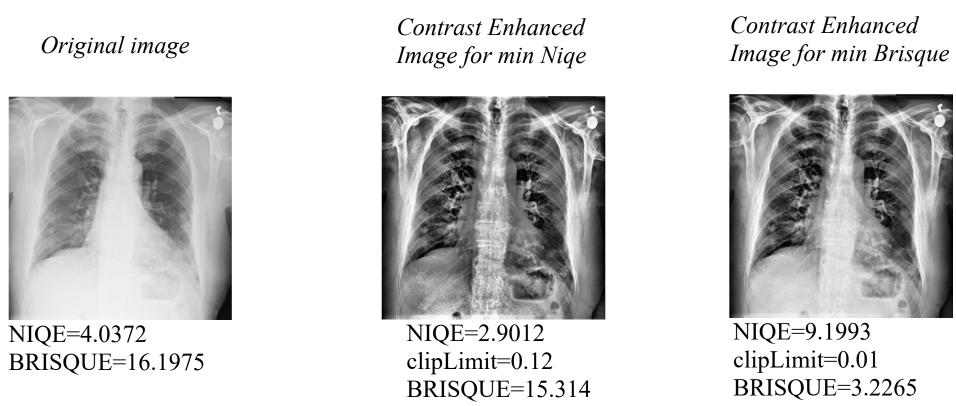


Fig. 5. Graphs of objective estimates for the converted images of the original '1.png' with the values distribution='rayleigh'; and 'clipLimi t'=[0, 0.2] in increments of 0.01 (BRISQUE estimates are marked in red, NIQE estimates in blue)



a *b* *c*

Fig. 6. Comparison of the result of the transformation: *a* – the original image; *b* – by the CLAHE method (distribution='rayleigh') with a minimum NIQE score(cliplimit=0.12);
c – with a minimum BRISQUE score (cliplimit=0.01)

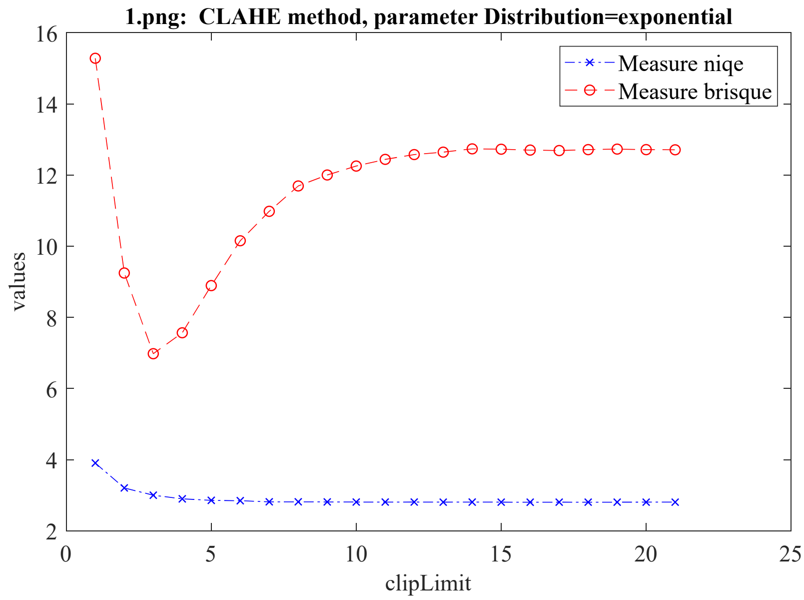
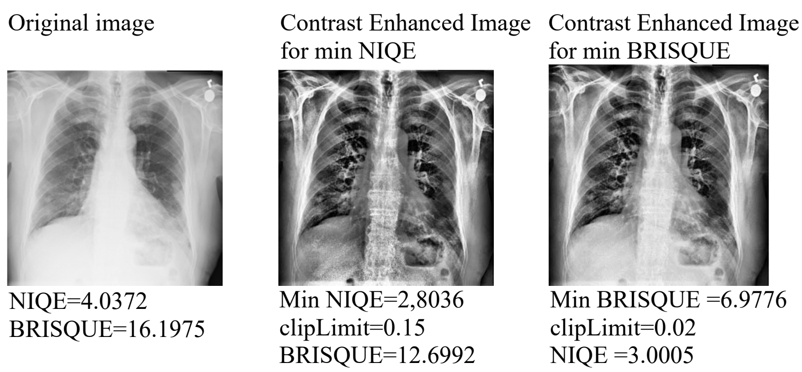


Fig. 7. Graphs of objective estimates for the converted images of the original '1.png' with the values distribution='exponential'; and 'clipLimit'=[0.02] in increments of 0.01 (BRISQUE estimates are marked in red, NIQE estimates in blue)



a *b* *c*

Fig. 8. Comparison of the result of the transformation: *a* — the original image; *b* — by the CLAHE method (distribution='exponential') with a minimum NIQE score(cliplimit=0.15); *c* — with a minimum BRISQUE score (cliplimit=0.02)

The estimates of the remaining similarly transformed test images are shown in Table 2. Here are the non-reference estimates of the original image and the results of the conversion by the CLAHE method with the selected values of the distribution parameter. For each of the values of this parameter, the minimum NIQE and BRISQUE estimates are determined, and the corresponding values of the cliplimit parameter and estimates for them.

Table 2

Comparison of the values of non-reference estimates of the original image and transformed images by the CLAHE method when changing the values of the distribution and cliplimit parameters

No. Image	Evaluation of the original image		Distribution	NIQE evaluation options			BRISQUE evaluation options		
	NIQE	BRISQUE		min NIQE	cliplimit for min NIQE	BRISQUE for min NIQE	min BRISQUE	cliplimit for min BRISQUE	NIQE for min BRISQUE
1	2	3	4	5	6	7	8	9	10
1	4.0372	16.1975	'rayleigh'	2.9012	0.1200	15.314	9.1993	0.0100	3.2265
			'exponential'	2.8036	0.1500	12.6992	6.9776	0.0200	3.0005
2	4.2881	18.7059	'rayleigh'	3.0420	0.0800	15.7290	8.9939	0.0100	3.3514
			'exponential'	3.0024	0.0800	14.7401	7.2666	0.0100	3.3447
3	4.1413	10.4101	'rayleigh'	3.1609	0.0700	14.4351	6.6493	0.0100	3.4322
			'exponential'	3.0930	0.0700	15.6488	9.0976	0.0100	3.3438

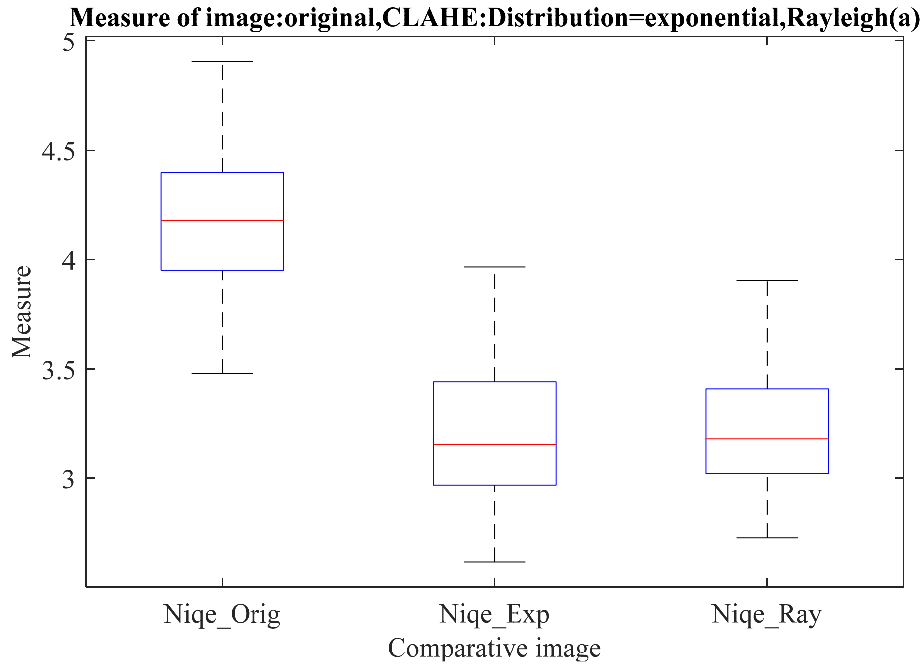
Continuation of Table 2

1	2	3	4	5	6	7	8	9	10
4	4.2956	13.0724	'rayleigh'	3.2971	0.1700	17.8653	13.0724	0.0100	3.5975
			'exponential'	3.2193	0.1700	19.9392	13.0724	0.0100	3.5217
5	4.3203	25.7744	'rayleigh'	2.9495	0.0500	27.6091	25.7744	0.0100	3.3356
			'exponential'	2.9055	0.0600	26.7410	22.3760	0	4.2776
6	4.8023	29.9513	'rayleigh'	3.9037	0.1300	17.1803	16.9361	0.2300	3.9085
			'exponential'	3.9655	0.1600	19.0927	18.9781	0.2100	3.9714
7	4.1236	32.9393	'rayleigh'	3.1985	0.0600	30.1764	29.7313	0.1400	3.2379
			'exponential'	3.2157	0.06	31.9325	31.4608	0.1800	3.2713
8	4.9052	20.7903	'rayleigh'	3.7177	0.2000	17.0425	16.8971	0.1800	3.7219
			'exponential'	3.6994	0.0400	21.0544	19.2853	0.2000	3.7114
9	4.2157	34.7177	'rayleigh'	3.4332	0.2000	25.9130	25.8693	0.1600	3.4634
			'exponential'	3.4773	0.2000	25.9445	25.9430	0.1900	3.4902
10	3.9375	30.1194	'rayleigh'	3.6873	0.1700	12.3793	11.9937	0.0400	3.7443
			'exponential'	3.6848	0.2000	14.0047	13.9701	0.0100	3.8829
11	3.5497	30.8850	'rayleigh'	3.1443	0.1800	14.0039	9.5838	0.0200	3.2766
			'exponential'	3.1448	0.1700	12.1949	7.8512	0.0200	3.2452
12	4.4868	28.2588	'rayleigh'	3.1433	0.1900	21.6859	20.5229	0.0100	3.6579
			'exponential'	3.1623	0.2000	20.5205	20.2735	0.0100	3.6320
13	3.4792	20.0601	'rayleigh'	2.8901	0.1900	16.1226	8.6904	0.0100	3.1919
			'exponential'	2.8575	0.1900	14.2448	4.2674	0.0100	3.2112
14	4.0547	25.4384	'rayleigh'	3.2687	0.2000	11.6555	6.0252	0.0200	3.4901
			'exponential'	3.3043	0.1500	12.3237	7.0433	0.0200	3.5533
15	3.9642	18.4571	'rayleigh'	2.9998	0.1100	4.5899	1.4626	0.0300	3.0682
			'exponential'	2.9344	0.1600	3.9475	2.2674	0.0300	2.9894
16	4.3019	28.3591	'rayleigh'	3.5744	0.1900	14.9727	11.2265	0.0300	3.6841
			'exponential'	3.5920	0.1600	15.8880	12.1109	0.0200	3.7419
17	3.6040	12.8876	'rayleigh'	2.7272	0.2000	23.1896	12.8876	0.0200	2.8659
			'exponential'	2.6170	0.2000	24.7692	12.8876	0.0200	2.7565
18	4.6498	10.9344	'rayleigh'	3.3828	0.0700	9.4383	7.0520	0.0200	3.4147
			'exponential'	3.4036	0.0400	9.8683	6.6668	0.0100	3.5684
19	3.8410	19.6463	'rayleigh'	3.1596	0.1500	23.4965	13.9484	0.0100	3.3539
			'exponential'	3.0731	0.1700	23.4218	17.2282	0.0100	3.3345
20	4.4724	20.6639	'rayleigh'	3.2127	0.1400	12.5477	10.2899	0.0200	3.4083
			'exponential'	3.1067	0.1300	10.3700	10.3700	0.0300	3.2490

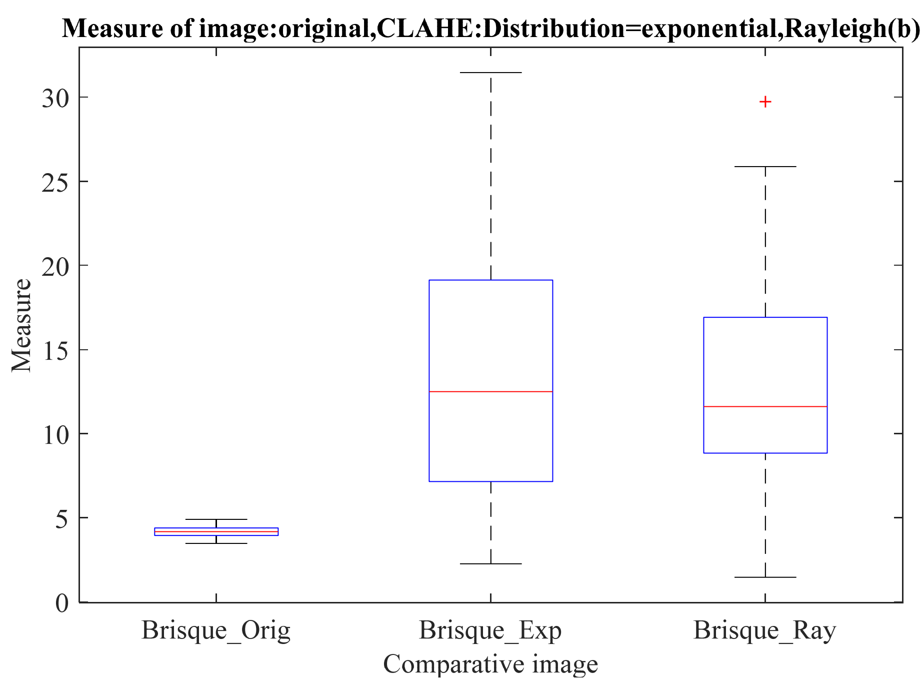
According to Table 2, it can be seen that changing the values of the distribution and cliplimit parameters, when performing the adaptive equalization method with contrast restriction, gives positive results. Analyzing the values of this table, you can give preference to the value of the distribution='exponential' parameter for certain values of the cliplimit parameter. This is confirmed by the values of the non-reference ratings NIQE and BRISQUE, which decrease in value when improving the contrast of medical images. As laboratory studies have shown, in many cases the NIQE score more accurately corresponded to the visual estimates of the transformed images. In Fig. 9, you can see a block diagram of the data distribution of Table 2, where the estimates of the original image are compared with the minimum estimates of the transformed images. The minimum estimates of each transformation by the CLAHE method with the values of 'exponential' and 'rayleigh' of the distribution parameter are shown using a boxplot.

Fig. 9 shows the minima, maxima, medians, lower and upper quartiles of the NIQE (top) and BRISQUE (bottom) ratings. The box with a mustache in Fig. 9, *a* shows a decrease in the NIQE score of the transformed images compared to the estimates of the original images, which is consistent with the visual perception of an increase in image contrast. At the same time, using the distribution='exponential' parameter gives slightly lower estimates. The box with a mustache in Fig. 9, *b* shows that the values of the BRISQUE score are increasing, which means that the quality of the images is deteriorating. Fig. 10 shows a box with a mustache for the cliplimit parameter.

Boxplot in Fig. 10 allows you to see that 50 % of the values of the cliplimit parameter in the distribution distribution=‘exponential’ falls in the range [0.095; 0.19], and in the distribution distribution=’rayleigh’ falls in the range [0.075; 0.18]. Therefore, to increase the contrast of X-ray images, it is recommended to use the range of values of the cliplimit parameter [0.1; 0.18], on average about 0.16.



a



b

Fig. 9. Comparison of the original image with CLAHE (distribution method:‘exponential’,’rayleigh’) transformation results:
a — with minimum NIQE scores; *b* — with minimum BRISQUE scores

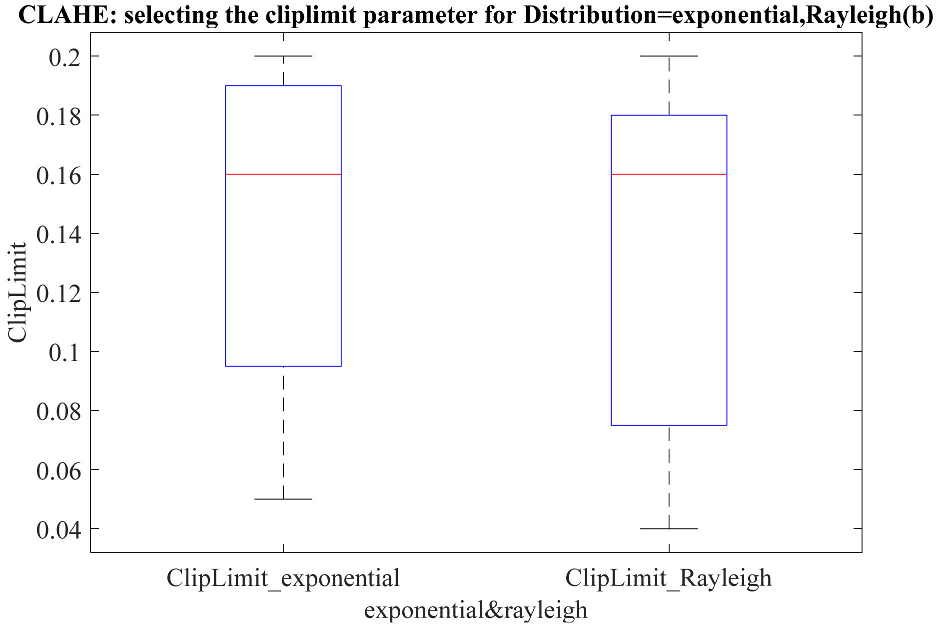


Fig. 10. Selecting the values of the cliplimit parameter of the transformation by the CLAHE method with the distribution parameters equal to 'exponential' (left) and 'rayleigh' (right)

6. Discussion of the results of contrast enhancement of X-ray medical images

This study examines the effectiveness of a combination of two different image enhancement methods. In the experiments, several hundred X-ray images from the Kaggle database were used [12], some of which visually improved when converting brightness by gamma correction without difficulty, and some after conversion took a darker shade, and the image quality remained low. When working with such images, there were difficulties in improving the contrast by gamma correction. In order to achieve better contrast before applying gamma correction, it was proposed to apply adaptive histogram equalization with contrast restriction. By correctly selecting the necessary input and output parameters of this transformation, we obtain the best visual contrast enhancement of the X-ray image (Fig. 3). The implementation of the method of adaptive equalization of the image histogram is justified by the choice of the values of the distribution and cliplimit parameters (Table 2). Choosing the value of the distribution='exponential' parameter improves the contrast between objective (Fig. 9) and subjective assessments at the same time. The analysis of the data in Table 2 allows you to select the values of the cliplimit parameter (Fig. 10). It is experimentally proved that it is preferable to use the CLAHE transformation with the values of the distribution='exponential' parameters, the values of the cliplimit parameter should be selected from the range [0.095; 0.18], on average about 0.16. The experiments performed showed that the combination of contrast limited adaptive histogram equalization and the gamma correction method significantly increases the contrast of X-ray images (Fig. 3, 4, 6, 8). Also, during the research, it was determined that the NIQE measure should be used for an objective assessment of the quality of X-ray images. It correlates more than the BRISQUE score with the subjective score. The peculiarity of the proposed method and the results obtained in comparison with the methods of other researchers [2–11] is the use of quantitative assessment of the contrast change of the transformed images. Objective assessments allow us to identify the limitation of the range of input and output parameters of the methods used. The limited number of estimates of contrast enhancement is a disadvantage of this study. It is advisable to develop this study with the inclusion of other suitable non-reference estimates, which requires new experimental studies.

During the experiments, light, dark and normal X-rays were processed. The application of the objective evaluation method to the processed images showed the following results. As a result of the study of options for converting test images, it is recommended to obtain X-ray images with maximum contrast:

– build a histogram of the image and determine its overall brightness level;

– apply the procedure of adaptive equalization of the image histogram with a contrast restriction, select 'exponential' with the value of the distribution parameter and select the values of the cliplimit parameter from the interval [0, 0.02] with a step of 0.01;

– evaluate all transformed images with a non-reference NIQE score and determine the image corresponding to the minimum NIQE score;

– after applying the CLAHE method, apply the *imadjust* function:

– if the original image *I* contains more light shades, then select the input parameters for the *imadjust* function in the following form:

$$J=imadjust\,(I,\,[0,\,high\_in],\,[0,\,1],\,\gamma),$$

where $0.4 \le high\_in \le 0.7$, $1.5 \le \gamma \le 3$ give better results;

– if the original image *I* contains more dark shades, then select the input parameters for the *imadjust* function in the following form:

$$J = imadjust\ (I,\ [low\_in,\ 1],\ [0,\ 1],\ \gamma),$$

where $0.4 \le low\_in \le 0.7$, $1.5 \le \gamma \le 3$.

As a result of the performed studies, it is shown that it is advisable to use a combination of the gamma correction method with the method of adaptive histogram equalization, in which contrast enhancement is limited in order to avoid the occurrence or amplification of noise in the image.

7. Conclusions

1. The study analyzes the possibilities of the methods of gamma correction and CLAHE to enhance the contrast of X-ray images. In the course of the experiments, the values of the necessary parameters were selected, in which subjective and objective assessments equally showed a positive result of improving the quality of X-ray images. Experiments have proved the feasibility of using a combination of the gamma correction method with contrast limited adaptive histogram equalization.

2. As a result of the experimental studies carried out, a method for using a combination of the gamma correction method with adaptive histogram equalization with contrast restriction has been formulated. This technique provides for the performance of contrast enhancement of X-ray images in two stages. At the first stage, the original image is transformed by the CLAHE method with the selected parameters, the second stage improves the resulting image by gamma correction. Experimental results have shown that the proposed technique allows obtaining X-ray images with enhanced contrast.

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