Application of the Clahe Method Contrast Enhancement of X-Ray Images

Omarova G. S[1], Aitkozha Zh.Zh[3], Nuridinov O[6]
Department of Information Systems
L. N. Gumilyov Eurasian National University
Nur-Sultan, Republic of Kazakhstan

Bekbolatov S[4]
Department of Information Systems
Taraz Regional University Named after M.KH. Dulaty
Taraz, Republic of Kazakhstan

Starovoitov V.V[2]
The Laboratory of System Identification
United Institute of Informatics Problems of the National Academy of Sciences of Belarus
Republic of Belarus, Minsk

Ostayeva A.B[5]
Department of Informatics and Information and Communication Technologies
Korkyt Ata Kyzylorda University
Kyzylorda, Republic of Kazakhstan

***Abstract*—Due to the nonlinearity of the luminance function produced by many medical recording devices, the quality of medical images deteriorates, which creates problems in the visual research work of physicians. X-rays can be taken as an example. This article examines methods of improving the contrast of graphic images methods of improving the quality of X-ray images. The research was carried out in several stages. Attempts were made to increase the contrast of several dozen X-ray images to select the best image brightness using brightness conversion methods in the MATLAB system. Contrast enhancement was observed during the experiments, resulting in the selection of a brightness range corresponding to the visual contrast enhancement. The selection of variables γ for the selected brightness range of the image was performed. The possibilities of the image histogram equalization method were considered. To obtain the best result before performing gamma correction the method of X-ray image histogram equalization is suggested. An enhancement version of this algorithm is presented because of the comparison. Application of the adaptive histogram equalization algorithm with contrast limitation provides a visual effect of improving the contrast of X-ray images. The NIQE and BRISQUE evaluation functions, which do not use reference images, are used to objectively quantify the conversion results.**

Keywords*—Digital X-ray image; image quality assessment; image enhancement; contrast enhancement; luminance transformation; adaptive image histogram equalization

I. Introduction

This One of the most powerful tools of modern informatics is medical imaging. Medical imaging is used to accurately and timely diagnose health problems, allowing patients to be treated more effectively. Nowadays, digital medical images are composed of many millions of pixels, which allows them to be considered big data. In some cases, there is a need to enhance the quality of medical images. However, in digital radiography, this may require increasing the radiation dose to the patient. Therefore, the goal of medical imaging is not to obtain a perfect image, but to obtain an image that is sufficient in terms of diagnosis concerning a particular medical problem and that causes minimal harm to the patient.

The essence of methods to enhance the quality of X-ray images is as follows: apply some mathematical methods to low contrast images and enhancement the quality of the digital medical image for a more accurate diagnosis of health problems.

II. Literature Review

In reviewing the experience of other researchers in this field, methods considered in the foreign literature have been studied. The paper [1] deals with contrast enhancement based on internal image decomposition, using Bregman split algorithm and CLAHE (Contrast limited adaptive histogram equalization). The authors show an enhancement meant in the images by evaluating the illumination and reflection levels using an internal image decomposition. A good contrast enhancement is obtained, but the proposed method is only for contrast enhancement and cannot be used for techniques like surface texture change, object insertion, etc.

In [2] Cheolkon Jung discusses the optimized perceptual tone mapping for contrast enhancement of images. The proposed method focuses on human visual attention by constructing a luminance histogram and performs contrast enhancement. The advantage of the method is that it enhancements the performance without excessive contrast enhancement. Contrast enhancement by this method requires more time compared to HE (Histogram equalization), CLAHE methods.

S.S. Haung [3] has proposed an effective method to change the histograms and enhance the contrast of digital images. This paper presents an automatic transformation method that enhancements the brightness of darkened images using gamma correction and brightness pixel probability distribution. It has been used to enhance the video data. The method proposed in the paper uses the differences between the frames to reduce the computational complexity. Experimental results have shown that the proposed method produces enhanced images of comparable or higher quality than those obtained using other methods.

M. Shakeri [4] proposed an algorithm for contrast enhancement based on local histogram equalization. The peculiarity of the algorithm is to determine the number of subhistograms and to separate the histogram based on saturation. The algorithm worked in three stages. Initially, the estimation of the number of clusters for image brightness levels is done using histogram alignment. In the next step, the image luminance levels are clustered and finally, the contrast enhancement for each cluster is included separately. The algorithm is compared with other methods based on quality and quantity measurements. The application of the method produces natural-looking images and enhanced 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 work [5] the authors have proposed a new method for improving medical images. First, the original medical image is decomposed into an NSCT (contour transform without subsampling) region with a low-frequency subband and several high-frequency sub-bands. A linear transformation is then used for the luminance coefficients of the low-frequency sub-band. An adaptive thresholding method is used for noise reduction of the coefficients of the high-frequency sub-bands. All sub-bands were then reconstructed into spatial regions using the inverse NSC transform. Next, unsharp masking was applied to increase the clarity of the details of the reconstructed image. Experimental results show that the proposed method outperforms other methods in terms of such characteristics as image entropy and PSNR (peak signal to noise ratio).

In [6] paper, the social network optimized approach for image fusion for contrast enhancement and brightness preservation is discussed. The social network optimization algorithm creates two quality images, one with better contrast, and increased entropy, and the second image with an increased peak signal-to-noise ratio. The two images are combined to produce an effective image later. Comparisons were made using HE, and linear contrast stretching. The results show that the proposed method provides a better peak signal-to-noise ratio, preserves brightness, and increases the contrast of any given image, resulting in a high-quality visual effect.

However, the number of edge pixels of this technique is large, while the fit value is smaller.

In [7], Se EunKim proposes an entropy-based method for contrast enhancement in the wavelet domain. Initially, he uses local entropy scaling in the wavelet domain to obtain the desired contrast. Mathematical methods were used, and then a color enhancement method was developed in the HSI (from hue, saturation, lightness (intensity)) color space. The algorithm worked in two steps: modifying the low frequencies in the wavelet domain and scaling the HSI color space by increasing the intensity component so that images in low light get detailed color information without any further processing. The peculiarity of the algorithm is that it is used in the HSI color space and provides an increase in the contrast of the image.

Huang Lidong [8] proposed a combination of adaptive histogram equalization with limited contrast and discrete wavelet transform to enhance the image. The algorithm works in three stages. First, the original image is allocated to low- and high-frequency components using a wavelet transform. The low-frequency coefficients are enhancements using the CLAHE method, while the high-frequency coefficients remain unchanged. When the wavelet transform is reversed, the image is mounted successfully. The proposed method is applicable for improving the local details of the image, preserving the details well, and suppressing noise. But the high-frequency component, which contains most of the noise in the original image, remains unchanged.

The authors of [9] propose a high-speed quantile-based histogram equalization (HSQHE) to preserve brightness and enhance contrast in the image. Contrast enhancement by this method is suitable for high-contrast digital images. Recursive segmentation of the histogram is not performed, so minimal time is required for segmentation. Entropy metrics are used to estimate PSNR of contrast enhancement. AMBE (Absolute Mean Brightness Error) is used to estimate brightness preservation. HSQHE preserves image brightness more accurately in a shorter time interval, but a high PSNR value is achieved only for certain images.

In [10], the authors propose a histogram modification scheme with entropy maximization. The method of histogram modification by entropy maximization divides the global histogram alignment into two stages: the pixel populations emergence (PPM) stage, which corresponds to the entropy maximization rule, and the gray-levels distribution (GLD) stage. The method gives good enhancement ments and avoids reinforced noise and distortions in the image, but there is a problem with excessive contrast stretching.

The proposed methods confirm the necessity of non-linear image brightness transformation methods for contrast enhancement, but it requires detailed study for more informative images after processing.

III. Image Enhancement Techniques

Image enhancement techniques involve performing such transformations on the original image that lead to a result that is more suitable for a particular application [11]. 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 enhance the contrast of a medical image, an evaluation of the result is necessary. Objective quality assessment algorithms are divided into benchmark and non-benchmark. The different reference criteria use a comparative quality assessment when the reference image is usually known to look like, and its characteristics are known [13]. When dealing with low-contrast medical images, there are no benchmarks for comparison. Therefore, it is necessary to select those evaluation options that do not require a reference image.

Image enhancement approaches fall 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 involve changing the images after the Fourier transform.

Let us consider some methods related to spatial processing methods. Spatial methods are described by the equation [12]:

$$g(x, y) = T[f(x, y)], \quad (1)$$

where f (x, y) is a function describing the original image, g (x, y) is the transformed image, and T is an operator over f defined in some neighborhood of a pixel with coordinates (x, y). The neighborhood of a pixel is understood as a square or rectangular area that is a subset of the image and is centered relative to the given pixel. The simplest version of the T operator 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 conversion.

Histogram transformations are divided into the following groups: linear logarithmic and power transformations. Histogram alignment 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 enhance image quality, it is necessary to increase such parameters as brightness range, contrast, sharpness, and sharpness. In combination, these parameters can be enhanced by aligning the histogram of the image. Histogram equalization algorithms are widely used to enhance the processed digital grayscale image. In general, such algorithms are simple to implement, have relatively low computational cost, and yet show high efficiency. The essence of such algorithms is to adjust the levels of the halftone image according to the probability distribution function of a given image (2) and, as a result, the dynamic range of brightness distribution increases. This leads to enhancement meant of visual effects, such as: brightness contrast, sharpness, and clarity.

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

$$H(j) = 255 \sum_{i=0}^{j} P(i) \quad (2)$$

where *P(i)* is the probability of the appearance of a pixel with brightness *i*, the normalized function of the histogram of the original image, *j* are the pixel coordinates of the processed image, *H(j)* is the transformed image [12]. Histogram equalization algorithms are divided into the following two types: local (adaptive) histogram equalization and global histogram equalization. In the global method, one chart is built, and the histogram of the entire image is equalized. In the local method, many 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 enhancements, which makes it possible to obtain better processing results in general.

An enhancement version of the above algorithm is the Contrast limited adaptive histogram equalization (CLAHE) algorithm. The main feature of this algorithm is the limitation of the histogram range based on the analysis of the pixel brightness values in the processed block (3), thus the resulting image looks more natural and less noisy [14].

$$da = \frac{n_c}{n} \quad (3)$$

where *da* is the increment factor of the value of the histogram function, *nc* is the number of pixels that exceed the threshold value. It is worth noting that the classic CLAHE algorithm uses bilinear interpolation to eliminate boundaries between processed blocks. The *imadjust* function is the basic tool in the MATLAB package for converting the brightness of grayscale 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 (I).

J =imadjust (I, [low_in, high_in], [low_out, high_out]).

J =imadjust (I, [low_in, high_in], [low_out, high_out], γ) (4)

The imadjust function converts the intensity values of the grayscale 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 the I image, then applies a linear contrast stretch.

The function J = imadjust(I, [low_in, high_in], [low_out, high_out]) converts the original brightness values I into new values 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 $\gamma = 1$, which corresponds to an identical mapping [9].

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

J=histeq(I, n) (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 transform 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. A true implementation of this method uses the maximum possible number of levels for n, which is 256. The CLAHE algorithm is implemented by the function adapthisteq, which has the following syntax:

J = adapthisteq(I,Name,Value) (6)

The Name input parameters can be:

- Number of rectangular context areas (tiles) into which adapthisteq divides the image, specified as a 2-element vector of positive integers;
- Contrast enhancement limit, specified as a real scalar in the range [0, 1];
- Number of histogram intervals used to build a contrast-enhancing transformation (256 by default);

- Desired histogram shape;
- Distribution parameter.

CLAHE works with small areas of the image, called tiles, rather than with the whole image. The contrast of each tile is increased so that the histogram of the output area roughly corresponds to the histogram specified by the "Distribution" value. Neighboring tiles are then combined using bilinear interpolation to eliminate artificially created borders. Contrast, especially in homogeneous areas, can be limited to avoid amplifying any noise that may be present in the image.

IV. Initial Data and Description of Experimental Studies

We use X-ray images from the Kaggle database [15] to experiment with the application of image brightness conversion methods. The experiment aims to increase image contrast to obtain more information about a pulmonologist's lung image representation. The essence of methods to improve the quality of medical images is to apply mathematical methods to low contrast images and improve the quality of digital medical images to improve diagnostic accuracy.

Many experiments were conducted to apply the imadjust function to several X-ray images to select the most appropriate input parameters. The values for (4) were chosen in increments of 0.1 in the range from 0 to 1 (Table 1.).

The non-referential NIQE and BRISQUE evaluation functions were used to determine how much contrast was enhanced. The NIQE (Naturalness Image Quality Evaluator) and BRISQUE (Blind/Referenceless Image Spatial Quality Evaluator) functions are used in cases where no image reference is available. The NIQE (A) function compares the quality of image *A* relative to an abstract model image constructed from images of natural scenes. The BRISQUE (A) function compares the quality of image *A* with respect to another model image constructed from many images of natural scenes with certain distortions. The smaller the values of these functions, the higher the quality of the images.

TABLE I. SELECTION OF PARAMETER VALUES OF THE IMADJUST FUNCTION

Image title	Selected imadjust options	Original Score		Post-conversion assessment	
		Niqe	***Brisque***	***Niqe***	***Brisque***
1.png	[0.4,1] [0,1]	4.0372	16.1975	3.4770	32.7370
2.png	[0.5,1] [0,1]	4.2881	18.7059	3.8257	32.7584
3.png	[0.2,1] [0,1]	4.1413	10.4101	3.9845	32.8306
4.png	[0.3,1] [0,1]	4.2956	13.0724	3.8182	32.3951
5.png	[0.2,1] [0,1]	4.3203	25.7744	3.8746	33.5517
Normal	[0.1,1] [0,1]	3.1248	18.1867	2.7623	25.4380
Pneumonia1	[0.3,1] [0,1]	3.0242	36.0416	2.6395	36.6267
Pneumonia2	[0, 1][0, 1]	2.7003	34.2984	2.7003	34.2984
Pneumonia3	[0.2,1] [0,1]	3.0398	13.8546	2.9204	33.3662
Pneumonia4	[0.2,1] [0,1]	3.0501	45.8458	2.9693	42.2854

During the experiments we have tried many brightness ranges of source images, for which the attempts to increase the contrast of the X-ray images gave a positive result both visually and quantitatively. Table 1 shows examples of imadjust function parameters in determining the most appropriate value of parameter γ. If γ<1, the resulting image will be lighter than the original one. However, in most cases there was no positive result in improving the image. If γ>1, the curve of transformation of brightness values will be concave, and the resulting image will be darker than the original one. 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] the ones with the best γ values were selected, then they were compared in the table. For example, for image 1.png the results are shown in Table 2.

Thus, according to the data in Table 2, you can determine the best value of the input parameters of the imadjust function. When you select these parameters, you can visually display the result of the transformation and compare it with the original image (Fig. 1).

Figure 1. shows the original image(a) and the result of applying the imadjust function with the selected parameters(b). Here the NIQE score for the original image is 4.0372 and for the transformed image the score is 3.3252. We can note the higher contrast of the transformed image and the NIQE score shows a lower value than that of the original image.

Table 3 shows the best score values for the 10 test images.

When selecting the value of parameter γ, in most cases of performing the function, the result of transformation did not give improvement and visual perception and in the quantitative assessment of the result. For example, Figure 2 shows the results of the transformation of the original image 4.png.

TABLE II. RESULTS OF APPLYING THE PARAMETER Γ

Imadjust input parameters	Estimates for γ = 1		Best gamma value	Estimation	
	Niqe	***Brisque***		***Niqe***	***Brisque***
[0.2 1] [0 1]	3,8665	13,0019	γ=4	3,3524	16,0788
[0.3 1] [0 1]	3,7775	14,7344	γ=2,5	3,3252	26,8559
[0.4 1] [0 1]	3,4770	32,7370	γ=2,5	3,3790	25,9206
[0.5 1] [0 1]	3,6238	31,6125	γ=2,5	3,5020	28,2055

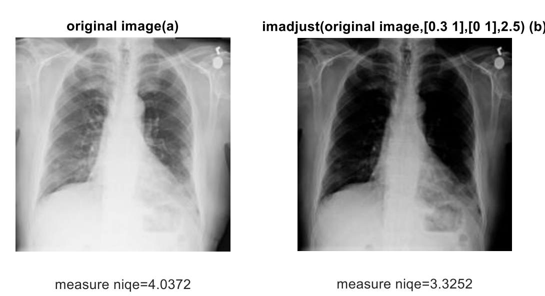

Fig. 1. Comparison of Imadjust ('1.png',[0.3, 1],[0, 1],2.5) (b) with the Original Image (a).

TABLE III. CHOICE OF Γ PARAMETER VALUE

Image title	**brightness options**	**Estimates for γ=1**		**The best value of the parameter γ**	**Niqe evaluation**	**Brisque Evaluation**
		Niqe	***Brisque***			
1.png	[0.3 1] [0 1]	3,7775	14,7344	γ=2.5	3,3252	26,8559
2.png	[0.4 1] [0 1]	3.9106	32.5165	γ=2	3.6851	22.3536
3.png	[0.2 1] [0 1]	3.9845	32.8306	γ=2	3.8189	25.2399
4.png	[0.2 1] [0 1]	4.1986	36.9663	γ=2	3.8848	25.4878
5.png	[0.2 1] [0 1]	4.0250	37.2250	γ=2	3.8306	31.3175
N	[0.2 1] [0 1]	3.2911	33.5240	γ=2	3.3236	21.5805
P	[0.3 1] [0 1]	2.6395	36.6267	γ=1.5	2.6767	37.6345
P	[0 1][0 1]	3.2048	41.9046	γ=2.5	3.2404	41.8697
P	[0.2 1] [0 1]	2.9204	33.3662	γ=2	2.5273	21.3953
P	[0.2 1] [0 1]	2.9693	42.2854	γ=2	3.0508	39.3603

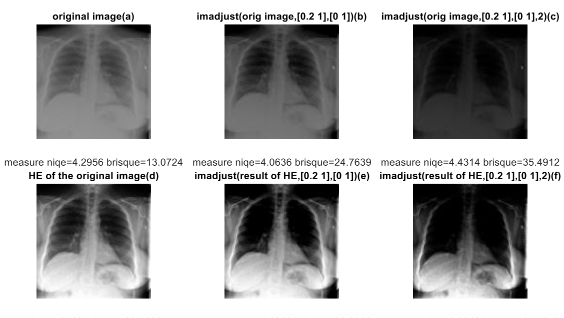

Fig. 2. Original Image (a) and its Transformed Versions with Estimates (b)(c)(d)(e)(f).

Applying histogram equalization (5) of the original image before testing the imadjust function with the choice of the parameter γ, gives the result of enhancement image contrast (Table 4).

In the following experiment, histogram equalization techniques are applied to several images, comparing their results with the quality of the original image. For example, for the above image 4.png (a), the application of histogram equalization (b) and adaptive histogram equalization with contrast restriction (c) are shown in Figure 3.

Figure 4 shows the results of similar actions for another image person9_bacteria_39.jpeg. It can be seen in the figures that the application of the adaptive histogram equalization method with contrast restriction (c) compared to the HE images result (b) visually gives a better result, but the NIQE and BRISQUE estimates do not always match.

TABLE IV. IMAGE ESTIMATES AFTER HISTOGRAM EQUALIZATION

Brightness conversion	**Estimates**	
	Niqe	**Brisque**
source image(4.png)	4.2956	13.0724
imadjust(original,[0.2 1],[0 1])	4.0636	24.7639
imadjust(source,[0.2 1],[0 1],2)	4.4314	35.4912
Alignment of the histogram of the original image	4.2516	22.1638
imadjust(original aligned,[0.2 1],[0 1])	4.1986	36.9663
imadjust(source aligned,[0.2 1],[0 1],2)	3.8848	25.4878

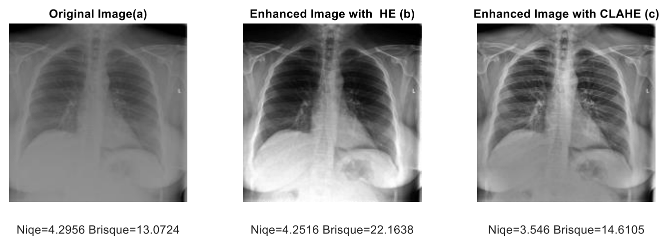

Fig. 3. Comparison of the Results of Applying Histogram Equalization Methods to the Image with Non-reference Estimates for Image 4.png.

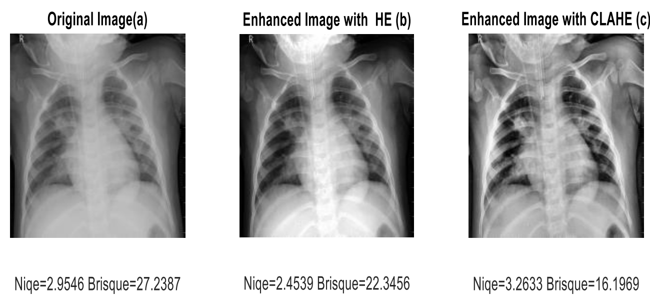

Fig. 4. Comparison of the Results of Applying Image Histogram Equalization Methods with Non-reference Estimates for the Person9_bacteria_39.jpeg (a) Image.

Table 5 shows the scores of 15 test images after applying the histogram equalization methods. In most cases, the results of applying the CLAHE method show a visual improvement in image contrast and a reduction in non-reference scores at the same time. In some cases, the estimates of the results of applying contrast-limited adaptive equalization do not decrease in value compared to the estimates of the original image.

As a result of analyzing the data in Table 5, it was decided that to improve the results of image contrast enhancement, it would be appropriate to replace the histogram equalization method with adaptive histogram equalization with contrast restriction. In the following experiment, function (6) was used to improve the contrast of image I in grayscale by transforming the values using adaptive histogram equalization with contrast restriction.

The application of this method was focused on the Distribution and SlipLimit parameters. The Distribution parameter takes the values 'uniform', 'rayleigh', 'exponential', which set the desired shape of the histogram. This parameter defines the distribution that adapthisteq uses as the basis for creating the contrast conversion function. The selected distribution should depend on the type of input image. For example, underwater images seem more natural when using the 'rayleigh' distribution.

TABLE V. IMAGE SCORES AFTER APPLYING HISTOGRAM EQUALIZATION METHODS

Image title	Original image		Histogram equalization result		CLAHE result	
	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	3.8508	27.6071
6.png	4.8023	29.9513	5.4088	40.3179	4.2207	28.3585
person1_bacteria_2.jpeg	3.0889	28.7698	2.5252	26.2216	3.3720	12.7819
person2_bacteria_4.jpeg	3.3458	19.7843	3.0630	20.6180	3.8828	24.8727
person3_bacteria_10.jpeg	2.8316	21.7251	2.9140	22.7425	3.1578	21.8798
person5_bacteria_15.jpeg	2.4308	34.7898	2.3427	32.8920	2.9593	28.5670
person6_bacteria_22.jpeg	2.6389	29.0688	2.3890	19.8988	3.3271	17.6235
person7_bacteria_24.jpeg	2.8125	28.8672	2.5647	28.1311	3.0936	2.2356
person8_bacteria_37.jpeg	2.7626	31.0623	2.3359	29.3576	2.3359	29.3576
person9_bacteria_39.jpeg	2.9546	27.2387	2.4539	22.3456	3.2633	16.1969
person17_bacteria_56.jpeg	2.6956	38.5977	2.6956	38.5977	2.6956	38.5977

The ClipLimit parameter is a contrast ratio that prevents oversaturation of the image, especially in homogeneous areas. These areas are characterized by a high peak on the histogram of a particular image fragment because many pixels fall within the same range of gray levels. Without clip limitation, the Adaptive Histogram Smoothing method can produce results that are, in some cases, worse than the original image. Its default value is 0.01.

The following steps were performed for several test X-ray images:

- To determine the optimal value of the 'clipLimit' parameter, we chose its values from the interval [0, 1] in steps of 0.01.
- Calculation of objective estimates for all transformed images.
- Plotting objective estimates for all versions of images.
- Determination of the minimal estimates NIQE and BRISQUE;
- Choosing the optimal visual representation of the image with the minimum objective estimates.

Construction of objective scores plots (Fig. 5) for several X-ray images showed that the values of cliplimit parameter can be limited from [0, 1] to [0, 0.2], as the following values were not informative. The minimal measures of the NIQE and BRISQUE estimates allow us to select images with improved contrast. This choice is related to the claim that the smaller the value of the non-reference score, the visually improved the image is. This assertion has been proven in previous studies, where a minimum NIQE score was more likely to coincide with an improved visual perception of the image.

Figure 6 shows a visual comparison of the original image (a) with the transformed one (b), where the clahe method is applied with the selected parameters and with the minimal NIQE score. Here the value of the distribution parameter is equal to 'rayleigh' and those obtained images are selected, at which the non-reference estimates had minimal values. For example, for the image 1.png the minimal estimate NIQE=2.9012 was received at cliplimit=0.12, and the BRISQUE=15.314 corresponds to it. For the image with minimal BRISQUE score equal to 9.1993 at value of cliplimit=0.01 the NIQE=3.2265 was defined. Here it can be noted that the decrease of the BRISQUE score in many cases does not correspond to the decrease of the NIQE score at which visual improvements were observed.

A visual comparison of the original image (a) with the CLAHE-transformed image (b) with minimal BRISQUE estimation is shown in Figure 7. Here the parameter distribution at value 'rayleigh' takes minimum BRISQUE value equal to 9.1993, which corresponds to NIQE=3.2365 at value of parameter cliplimit=0.01.

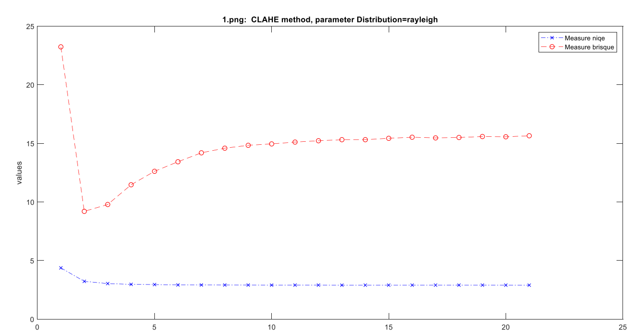

Fig. 5. Plots of Objective Estimates for the Transformed Images of the Original '1.png' with Distribution='Rayleigh'; and 'ClipLimit'=[0,0.2] with Step 0.01 (BRISQUE Estimates Marked in Red, Niqe Estimates Marked in Blue).

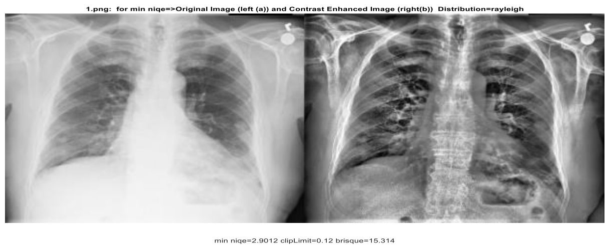

Fig. 6. Comparison of the Result of the Transformation of the Original Image (a) by the CLAHE Method (Distribution='Rayleigh', Cliplimit=0.12) (b) with the Minimum NIQE Estimate.

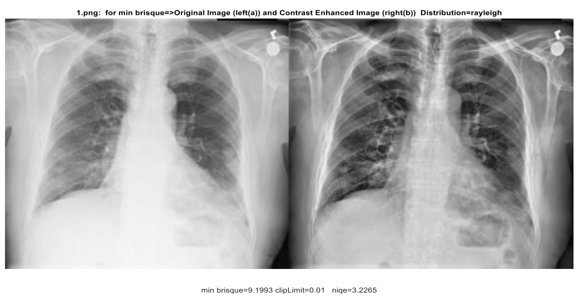

Fig. 7. Visual Comparison of the Original Image (a) with the Transformed CLAHE Method (Distribution='Rayleigh', Cliplimit=0.01) (b) and with the Minimum BRISQUE Estimate.

The plots of the objective estimates for the transformed images of the original '1.png' by the adaptive histogram equalization method with contrast constraint are shown in Figure 8. Here the distribution parameter takes the value 'exponential'; and the parameter 'clipLimit' receives values from the interval [0,02] with a step of 0.01.

A visual comparison of the original image (a) with the CLAHE-transformed image (b) with the minimum BRISQUE score is shown in Figure 9. Here the parameter distribution with 'exponential' value takes a minimum NIQE value of 2.8036, which corresponds to BRISQUE=12.6992 with the value of the parameter cliplimit=0.15.

A visual comparison of the original image (a) with the CLAHE-transformed image (b) with minimal BRISQUE estimation is shown in Figure 10. Here the parameter distribution at value 'exponential' takes minimum BRISQUE value equal to 6.9796, to which corresponds NIQE=3.0005 at value of parameter cliplimit=0.02.

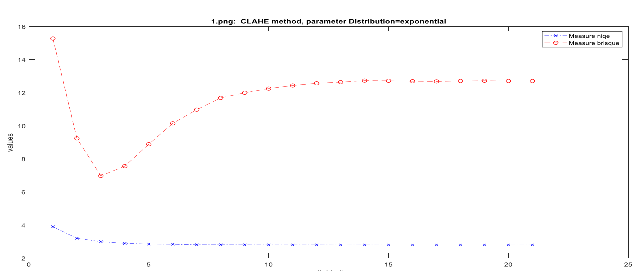

Fig. 8. Plots of Objective Estimates for the Transformed Images of the Original '1.png' with Values of Distribution='Exponential'; and 'ClipLimit'=[0,02] in Steps of 0.01 (BRISQUE Estimates Marked in Red, NIQE Estimates Marked in Blue).

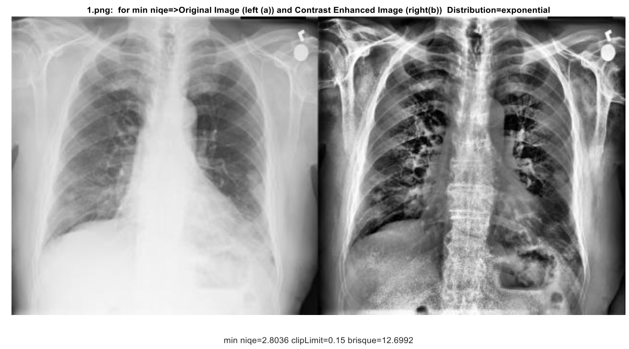

Fig. 9. Visual Comparison of the Original Image (a) with the Transformed CLAHE Method (Distribution='Exponential', Cliplimit=0.15)(b) and with the Minimum NIQE Estimate.

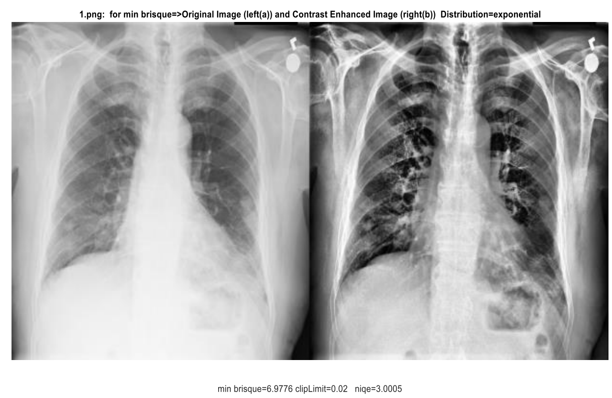

Fig. 10. Visual Comparison of the Original Image (a) with the CLAHE Transformed Image (Distribution='Exponential', Cliplimit=0.02) (b) with Minimum BRISQUE Estimation.

The results of similar actions performed on the rest of the test images are shown in Table 6. Here are the non-reference estimates of the original image and the CLAHE transformation results with the selected values of the distribution parameter. For each value of this parameter, the minimum estimates of NIQE and BRISQUE, and their corresponding values of the cliplimit parameter and estimates have been determined.

Table 6 shows the values of the obtained non-referential estimates of the original image and the transformed images using the CLAHE method. Changing the values of the distribution and cliplimit parameters, when performing the adaptive equalization method with contrast restriction, gives positive results. An analysis of the values in Table 6 gives a preference for the value of the 'distribution='exponential' parameter for certain values of the cliplimit parameter. This is evidenced by the NIQE and BRISQUE non-reference scores, which decrease in value as the contrast of medical images improves. As demonstrated by the laboratory studies performed, in many cases the NIQE score was more consistent with image improvement.

As a result of the performed laboratory studies, a combination of the gamma correction method and the adaptive histogram equalization method, in which contrast enhancement is limited to avoid causing or enhancing noise in the image, is considered appropriate.

TABLE VI. COMPARISON OF NON-REFERENCE ESTIMATES OF THE ORIGINAL IMAGE AND THE CLAHE-TRANSFORMED IMAGES WHEN CHANGING THE VALUES OF THE DISTRIBUTION AND CLIPLIMIT PARAMETERS

Image	Niqe (original)	Brisque (original)	distribution	min Niqe	for min Niqe, cliplimit	for min Niqe Brisque	min Brisque	for min Brisque, cliplimit	for min Brisque, Niqe
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
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	3.0889	28.7698	'rayleigh'	3.0759	0	33.8095	4.9285	0.0100	3.1913
			'exponential'	3.0337	0	29.4685	10.0346	0.0100	3.3622
8	3.3458	19.7843	'rayleigh'	3.2490	0	19.1865	19.1865	0	3.2490
			'exponential'	3.3083	0	13.8267	13.8267	0	3.3083
9	2.8316	21.7251	'rayleigh'	2.6969	0	28.6374	11.0289	0.0100	3.0216
			'exponential'	2.7980	0	21.5236	18.7296	0.0100	3.1852

V. CONCLUSION

During the experiment, X-ray images were used, some of which visually improved without difficulty during luminance conversion, some of which took a darker shade after conversion, and the image quality remained poor. When working with such images, it was difficult to improve the contrast using gamma correction. To achieve better contrast, an image histogram alignment was performed before applying gamma correction. This resulted in better results. Based on the final Table 3, we can conclude that the best results were achieved with the input parameters [0.2 1] [0 1] with $\gamma = 2$. As a result of research of test image transformation variants, to improve the contrast of X-ray images it is recommended first to apply the histogram equalization procedure and then imadjust transformation with the parameters ([low_in 1] [0. 1], 2), where 0.2<=low_in<=0.4. To improve the obtained results, it was decided to replace the histogram equalization with adaptive histogram equalization with contrast limitation. Because of applying this method, it was determined that the 'exponential' value is given preference when the distribution parameter is given a value values of the cliplimit parameter. It was also determined during the research that in most cases the quantitative measure of NIQE is more consistent with image improvement than the BRISQUE score when evaluating image quality.

REFERENCES

[1] Huanjing Yue, Jingyu Yang, Xiaoyan Sun, Feng Wu. Contrast Enhancement Based on Intrinsic Image Decomposition, IEEE Transactions on image processing 2017, 26(8), P.3981-3994.

[2] Cheolkon Jung, Tingting Sun. Optimized Perceptual Tone Mapping for Contrast Enhancement of Images, IEEE Transactions on circuits and systems for video technology 2017, 27(6), P. 1161-1170.

[3] S.S. Haung, F.S. Cheng, Y.C. Chiu. Efficient contrast enhancement Using Adaptive Gama Correction with Weighting Distribution. IEEE Transactions on Image Processing 2013; 22 (3): P.1032-1041.

[4] M.Shakeri, M.H.Dezfoulian, H.Khotanlou, A.H.Barati, Y.Masoumi. Image contrast enhancement using fuzzy clustering with adaptive cluster parameter and sub-histogram equalization", Elsevier Digital signal Processing 2017, P. 224-237.

[5] L.Liu, Z. Jia, J. Yang, N. Kasabov. A Medical Image Enhancement Method Using Adaptive Thresholding in NSCT Domain Combined Unsharp Masking. Wiley Periodicals, Inc. 2015, 25: P.199–205.

[6] Lalit Maurya, Prasant Kumar Mahapatra, Amod Kumar. A social spider optimized image fusion approach for contrast enhancement and brightness preservation, Elsevier Applied soft computing 2017, P.575–592.

[7] Se EunKim, JongJuJeon, IlKyuEom. Image contrast enhancement using entropy scaling in wavelet domain, Elsevier signal Processing 2016, P. 1-11.

[8] Huang Lidong, Zhao Wei ✉, Wang Jun, Sun Zebin, Combination of contrast limited adaptive histogram equalisation and discrete wavelet transform for image enhancement, IET Image Processing Journals 2015, Vol. 9, Iss. 10, P. 908–915.

[9] Mayank Tiwari, Bhupendra Gupta, Manish Shrivastava, Highspeed quantile-based histogram equalisation for brightness preservation and contrast enhancement, IET Image Process 2015, 9(1), P. 80–89.

[10] Zhao Wei, Huang Lidong, Wang Jun, Sun Zebin, Entropy maximisation histogram modification scheme for image enhancement, IET Image Process 2015, 9(3), P. 226–235.

[11] Gonzalez R., Woods R. Digital image processing. - 3rd edition, revised and supplemented. –Moscow: Technosphere, 2012. – 1104 p.

[12] Gonzalez R., Woods R., Eddins S. Digital image processing in Matlab. – M.: Technosphere, 2006.-616 p.

[13] Starovoitov F.V., Parameters of the distribution curve of local estimates as a measure of image quality / F. V. Starovoitov, V. V. Starovoitov // System analysis and applied informatics. – 2018. – No. 3. – pp. 26-41.

[14] Ma J., Fan X., Yang S.X., Zhang X.], Zhu X. Contrast Limited Adaptive Histogram Equalization Based Fusion for Underwatern Image Enhancement // Preprints [Электронный ресурс] 2017, URL: https://www.preprints.org/manuscript/201703.0086/v1.

[15] Https://www.kaggle.com/paultimothymooney/chest-xray-pneumonia.