ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

NO-REFERENCE QUALITY ASSESSMENT OF MEDICAL IMAGES USING CONTRAST ENHANCEMENT

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ABSTRACT

Contrast distortion is often a determining factor in human perception of image quality, but little investigation has been dedicated to quality assessment of contrast-distorted images without assuming the availability of a perfect-quality reference image. In many real-world applications, images are prone to be degraded by contrast distortions during image acquisition. Quality assessment for contrast-distorted images is vital for benchmarking and optimizing the contrast-enhancement algorithms. Visual study of medical images is essential for the diagnosis of many diseases. Various contrast enhancement methods such as histogram equalization, histogram modification methods, gamma correction, etc. are used to improve the contrast of medical images. Image quality evaluation is an integral part of the contrast enhancement and image enhancement processes. Quantitative measures of digital image quality make it possible to compare the applied processing methods and choose the best of them. The article studied methods for improving the quality of x-rays. The research was carried out in several stages. Attempts were made to increase the contrast of several tens of X-ray images in order to select the best image brightness using brightness transformation methods in the MATLAB system. Contrast improvement is supported by objective scores calculated by the NIQE and BRISQUE functions that do not require reference images. As a result of successive experiments, recommendations were proposed for selecting the parameters of the gamma correction method and the adaptive histogram equalization method, where contrast enhancement is limited in order to avoid the appearance or enhancement of noise in the image. The experiment is based on the algorithms of objective non-reference quality assessment NIQE and BRISQUE. A feature of this work is the use of objective non-reference estimates to determine the quality of images. The performed experiments allow to give preference to the NIQE assessment, since it corresponded to the results of image contrast enhancement.

Keywords: *Digital X-Ray Image, Image Quality Evaluation, Image Enhancement, Contrast Enhancement*

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 contrast enhancement of medical images is relevant.

2. LITERATURE REVIEW AND PROBLEM STATEMENT

Currently, there is a classification of methods and algorithms for assessing image quality, subjective and objective quality criteria. Subjective criteria for image quality are determined by a group of experts consisting of at least 15 people [2]. The subjective quality score ranges from 1 to 5, where the lowest value is assessed as “poor quality”, and it can also take continuous values from 0 to 100. The DMOS (difference mean opinion score) metric takes values from 0 to 100, where the quality images are better at lower values. According to the received expert estimates, a linear display of the value is created, which is determined on a quality scale, the range of which is from 1 to 100. If the result has a higher value, the quality of the tested image is considered to be worse. When using objective image quality criteria, the assessment is carried out without the participation of experts. To determine the degree of correspondence between objective and subjective assessments, the rank correlation coefficients of Kendall, Spearman, Pearson, the value of the standard deviation are used. It is believed that if high values of the correlation coefficients are determined simultaneously with a small value of the standard deviation, then the algorithm of the objective quality criterion will be good [3].

While getting acquainted with the experience of other researchers in this subject area, the methods considered in foreign literature were studied. In [4] article report a new large dedicated contrast-changed image database (CCID2014), which includes 655 images and associated subjective ratings recorded from 22 inexperienced observers. Also presented a novel reduced-reference image quality metric for contrast change (RIQMC) using phase congruency and statistics information of the image histogram. Validation of the proposed model is conducted on contrast related CCID2014, TID2008, CSIQ and TID2013 databases, and results justify the superiority and efficiency of RIQMC over a majority of classical and state-of-the-art IQA methods. Furthermore, combined aforesaid subjective and objective assessments to derive the RIQMC based Optimal Histogram Mapping (ROHIM) for automatic contrast enhancement, which is shown to outperform recently developed enhancement technologies.

In the article [5], proposed a framework to do quality assessment for comparing image enhancement algorithms. Not like traditional image quality assessment approaches, authors focused on the relative quality ranking between enhanced images rather than giving an absolute quality score for a single enhanced image. Authors construct a dataset which contains source images in bad visibility and their enhanced images processed by different enhancement algorithms, and then do subjective assessment in a pair-wise way to get the relative ranking of these enhanced images. A rank function is trained to fit the subjective assessment results, and can be used to predict ranks of new enhanced images which indicate the relative quality of enhancement algorithms. The experimental results show that their proposed approach statistically outperforms state-of-the-art general-purpose NR-IQA algorithms.

The authors of [6] propose a contrast-changed image quality (CCIQ) metric including a local index, named edge-based contrast criterion (ECC), and three global measures. In the global measures, entropy, correlation coefficient and mean intensity are exploited. Particle swarm optimization (PSO) algorithm is utilized for obtaining an optimal combination of these quantities. Although the presented method utilizes the original image, it cannot be considered as a full-reference metric, since the original image is not regarded to have the ideal quality. Authors concluded that it follows a new paradigm in image quality assessment. Experimental results in the work on the three benchmark databases, CID2013, TID2013 and TID2008 demonstrate that the proposed metric outperforms the-state-of-the-art methods.

In the article [7], the authors proposed a simple but effective method for no-reference quality assessment of contrast distorted images based on the principle of natural scene statistics (NSS). A large scale image database is employed to build NSS models based on moment and entropy features. The quality of a contrast-distorted image is then evaluated based on its unnaturalness characterized by the degree of deviation from the NSS models. Support vector regression (SVR) is employed to predict human mean opinion score (MOS) from multiple NSS features as the input.

Experiments based on three publicly available databases demonstrate the promising performance of the proposed method.

In the article [8] an Edge-based image quality measure (IQM) technique for the assessment of histogram equalization (HE)-based contrast enhancement techniques has been proposed that outperforms the Absolute Mean Brightness Error (AMBE) and Entropy which are the most commonly used IQMs to evaluate Histogram Equalization based techniques, and also the two prominent fidelity-based IQMs which are Multi-Scale Structural Similarity (MSSIM) and Information Fidelity Criterion-based (IFC) measures. The statistical evaluation results show that the Edge-based IQM, which was designed for detecting noise artifacts distortion, has a Person Correlation Coefficient (PCC) > 0.86 while the others have poor or fair correlation to human opinion, considering the Human Visual Perception (HVP). Based on HVP, this paper proposes an enhancement to classic Edge-based IQM by taking into account the brightness saturation distortion which is the most prominent distortion in HE-based contrast enhancement techniques. It is tested and found to have significantly well correlation (PCC > 0.87, Spearman rank order correlation coefficient (SROCC) > 0.92, Root Mean Squared Error (RMSE) < 0.1054, and Outlier Ratio (OR) = 0%).

In [9] the article proposed a new IQM which takes into account the perceived annoyance of noise due to excessive contrast enhancement. The evaluation results in this paper shows, that the proposed IQM outperforms other IQMs in study, including the prominent MSSIM.

In [10] proposed a very simple but effective metric for predicting quality of contrast-altered images based on the fact that a high-contrast image is often more similar to its contrast enhanced image. Authors first generate an enhanced image through histogram equalization. Authors then calculate the similarity of the original image and the enhanced one by using structural-similarity index (SSIM) as the first feature. Further, calculated the histogram based entropy and cross entropy between the original image and the enhanced one respectively, to gain a sum of 4 features. Authors learn a regression module to fuse the aforementioned 5 features for inferring the quality score.

In [11] authors devise a novel no-reference/blind quality assessment method for those contrast-distorted images. In the proposed method, authors characterize the image quality by deeply investigating multiple contrast distortion-relevant properties of the image, i.e., spatial characteristics, image histogram, visual perception characteristics and chrominance, which can describe the image quality more comprehensively and precisely. Accordingly, a series of quality-aware features are developed to characterize the contrast-distorted image quality properly. Support vector regression (SVR) is then employed to integrate all the extracted features and infer the image quality score. Extensive experiments conducted on the standard contrast-distorted image databases/datasets demonstrate that the proposed method achieves superior prediction performance to the state-of-the-art NR quality assessment models on evaluating the contrast-distorted image quality.

The authors of [12] 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 [13], the authors propose a no-reference quality metric for contrast-distorted images based on Multifaceted Statistical representation of Structure (MSS). The “Multifaceted” has two meanings, namely (1) not only the luminance information, but also the chromatic information is used for structure representation. This is inspired by the fact that the chromatic information on the one hand affects the perception of image quality as well, and on the other hand it changes along with the contrast distortions. Therefore, the chromatic information should be integrated with the luminance information for quality assessment of contrast-distorted images, a fact most existing quality metrics overlook; (2) regarding structure representation, three aspects, i.e. spatial intensity, spatial distribution, and orientation of structures are calculated, which is enlightened by the fact that the human visual system (HVS) is sensitive to the three aspects of structures. Specifically, the image is first transformed from RGB to the S-CIELAB color space to obtain a representation that is more consistent with the characteristics of the HVS, as well as to separate the chromatic information from the luminance. Then the statistical structural features are extracted from both luminance and chromatic channels. Finally, the back propagation

(BP) neural network is adopted to train a quality prediction model. Experimental results conducted on four public contrast-distorted image databases demonstrate the superiority of the proposed method to the relevant state-of-the-arts.

In studies of image evaluation algorithms [2-13], both well-known algorithms are considered, and new image evaluation algorithms are proposed. New types of non-reference evaluations are proposed, which are tested for evaluating images that have been transformed by contrast enhancement methods. The described image estimation algorithms have their advantages and disadvantages. They can be successfully used in various spheres of human activity. It should be noted that the number of studies related to the evaluation of medical images is limited. Medical images do not have standards for comparison, and for their evaluation it is necessary to select those ratings that correspond to visual improvements. This study differs from the studies reviewed in that the study of non-reference assessments is carried out simultaneously with the study of methods for improving medical images. Within the framework of this study, results have been achieved that, with the help of quantitative estimates, allow us to assess the change in contrast in the transformed images, to make a choice of the necessary parameters of image enhancement methods.

3. THE AIMS AND OBJECTIVES OF THE RESEARCH

The purpose of this article is to study image evaluation algorithms and determine their potential when choosing image contrast enhancement methods to enhance low-contrast X-ray images.

To achieve this goal, the following tasks were set:

- to study adaptive methods of contrast enhancement and apply non-reference image assessments to select their parameters;
- to develop a methodology for the use of adaptive contrast enhancement methods.

To select a contrast enhancement method, as well as its parameters, an image evaluation is required. The experiment is based on the algorithms for objective non-reference quality assessment NIQE and BRISQUE. Experiments use the assumption that given objective scores decrease in value as visual contrast increases.

4. MATERIALS AND METHODS OF RESEARCH

The object of our research is the process of increasing the contrast of the X-ray image. An increase in image contrast is achieved by comparing the results of using conversion methods with non-reference image estimates.

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; the methods of system analysis; the methods of mathematical modelling.

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;
– the X-ray images were used from the Kaggle database [16];
– 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 [14]. 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. 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.

Journal of Theoretical and Applied Information Technology
15th January 2023. Vol.101. No 1

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

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.

5. RESULTS OF THE STUDY OF IMAGE CONTRAST ENHANCEMENT METHODS

To perform experiments on the application of image brightness conversion methods, several dozen X-ray images from the Kaggle database were used [16]. The aim of the experiments is to find a method to increase the contrast of X-ray images of the 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.

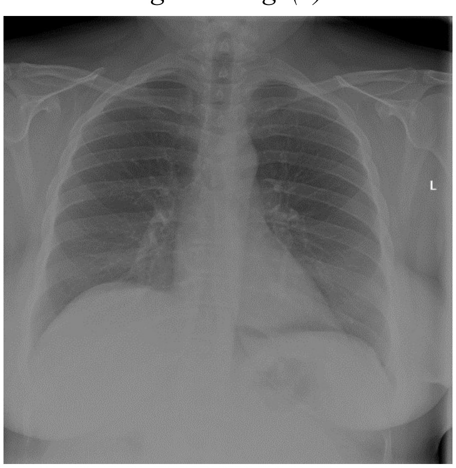
5. 1. Gamma Correction of X-Ray Images

A number of experiments have been carried out to apply the brightness conversion function of halftone images 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.

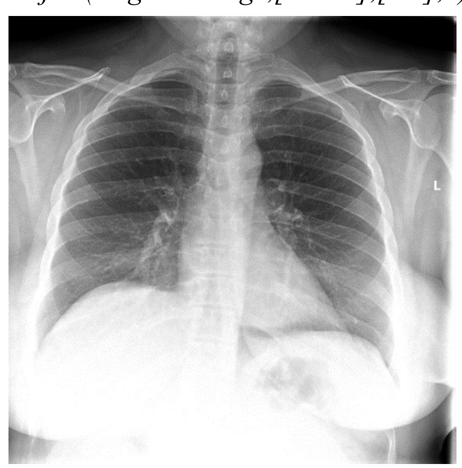
The evaluation functions NIQE (Naturalness Image Quality Evaluator) [17] and BRISQUE (Blind/Reference less Image Spatial Quality Evaluator) [18] are used in cases where there is no image standard. The NIQE (A) function compares the image quality of A relative to an abstract model image based on images 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).

Original image(a)



measure NIQE=4,2956

imadjust(original image,[0 0.55],[0 1],2)(b)



measure NIQE=3,4797

Figure 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

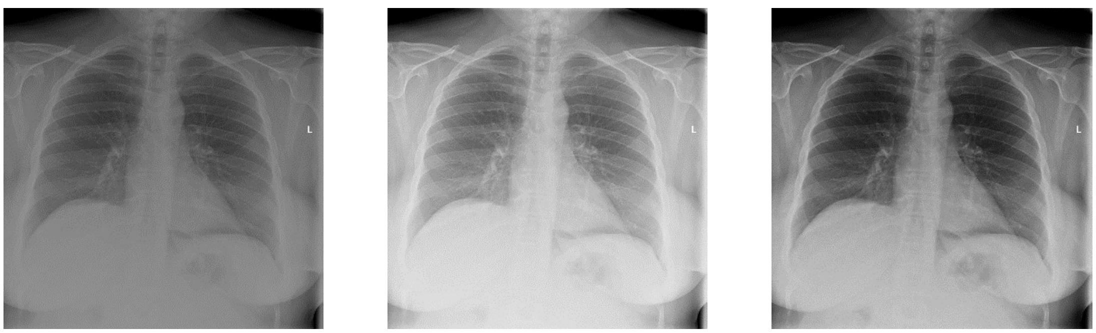
ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

image, as evidenced by a lower NIQE quantification value than that of the original image.

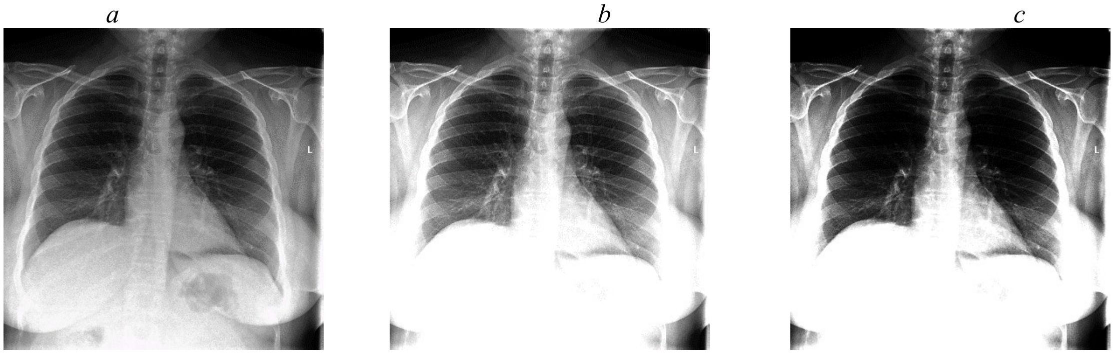
When choosing the value of the parameter γ, in most cases of using the imadjust function, the conversion result did not give a visual improvement, which was confirmed by quantitative estimates [19]. For example, Fig. 2 shows the results of converting the original 4.png image with different parameters.

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.



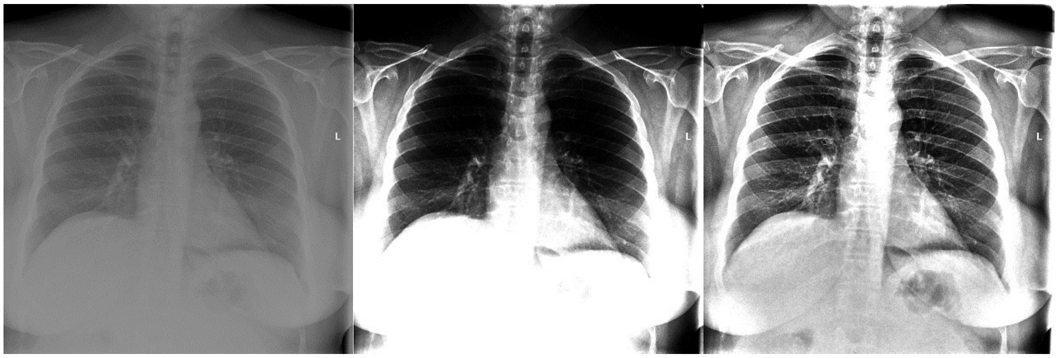
NIQE=4,2956 BRISQUE=13,0724 *a* | NIQE=3,8334 BRISQUE=12,1771 *b* | NIQE=3,5692 BRISQUE=11,4306 *c*



NIQE=4,2516 BRISQUE=22,1638 *d* | NIQE=4,5648 BRISQUE=33,6333 *e* | NIQE=3,926 BRISQUE=34,0816 *f*

Figure 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 the parameters [0, 0.65], [0, 1], γ=2

Applying the histogram equalization 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.



NIQE=4,2956 BRISQUE=13,0724 *a*

NIQE=3,926 BRISQUE=34,0816 *b*

NIQE=3,4044 BRISQUE=32,3527 *c*

Figure 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

The 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.

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**

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 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.

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. 4) 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. Here the distribution parameter takes the value ‘exponential’; and the 'clipLimit' parameter gets values from the interval [0,0.2] with a step of 0.01.

Journal of Theoretical and Applied Information Technology
15th January 2023. Vol.101. No 1

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

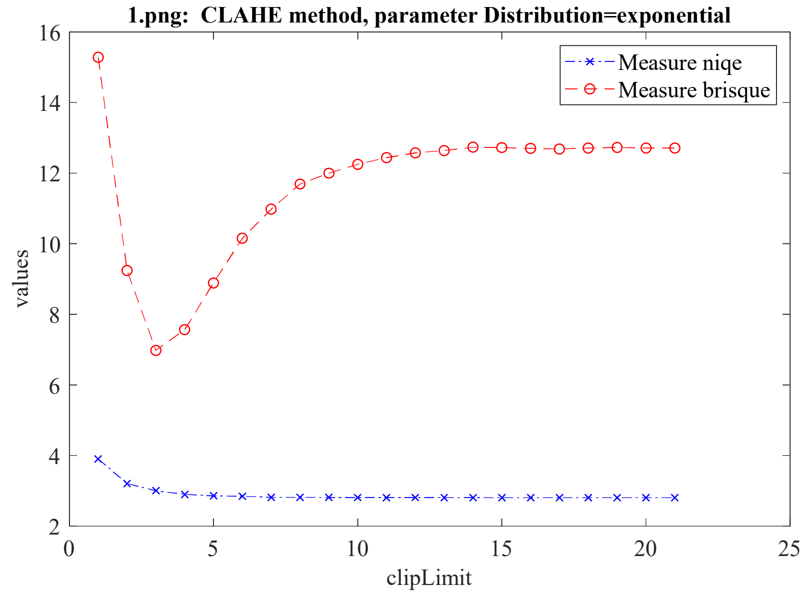


Figure 4: Graphs of objective estimates for the converted images of the original '1.png' with the values distribution='exponential'; and 'clipLimit'=[0,0.2] in increments of 0.01 (BRISQUE estimates are marked in red, NIQE estimates in blue)

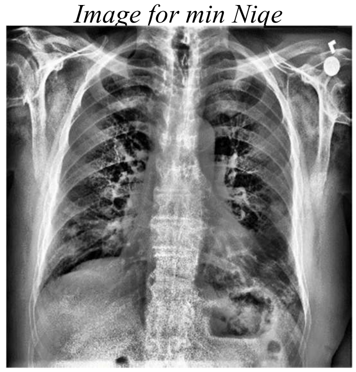
Fig. 5 shows a visual comparison of the original image Fig. 5, *a* with the transformed ones, where the CLAHE method is applied with the selected parameters and with the minimum NIQE score Fig. 5, *b* and the minimum BRISQUE score Fig. 5, *c*. Here the value of the distribution parameter is 'rayleigh' 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.

Original image

NIQE=4,0372,
BRISQUE=16,1975

a

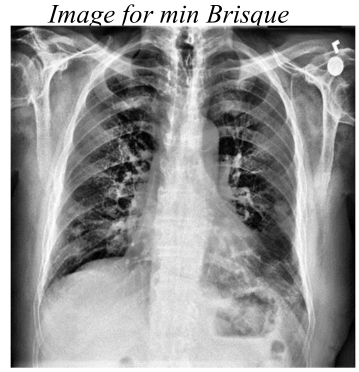
Contrast Enhanced Image for min Niqe



NIQE=2,9012,
clipLimit=0,12,
BRISQUE=15,314

b

Contrast Enhanced Image for min Brisque



NIQE=9,1993,
clipLimit=0,01,
BRISQUE=3,2265

c

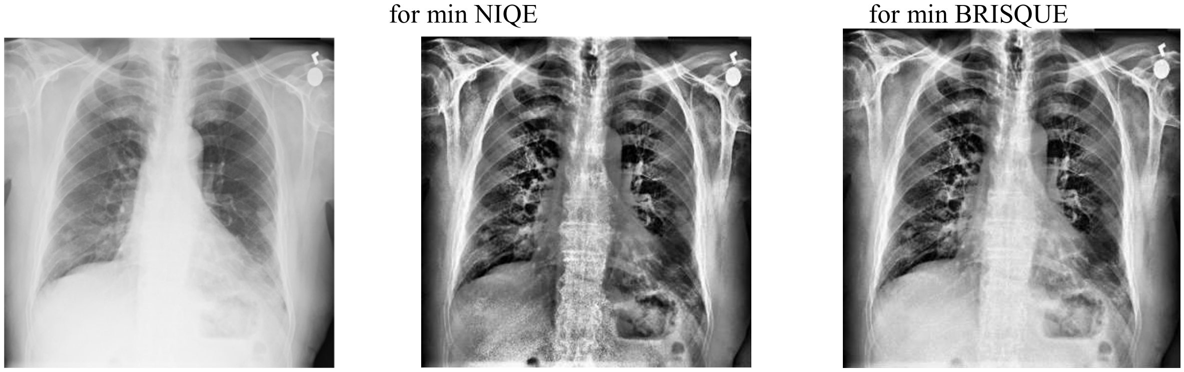
Figure 5: Comparison of the result of the transformation: a - the original image; b - by the CLAHE method (distribution='rayleigh') with a minimum NIQE score(cliplimit=0.12); c - with a minimum BRISQUE score (cliplimit=0.01)

Journal of Theoretical and Applied Information Technology
15th January 2023. Vol.101. No 1

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

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 '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.

Original image | Contrast Enhanced Image for min NIQE | Contrast Enhanced Image for min BRISQUE



NIQE=4,0372
BRISQUE=16,1975

Min NIQE=2,8036
clipLimit=0,15
BRISQUE=12,6992

Min BRISQUE =6,9776
clipLimit=0,02
NIQE =3,0005

a *b* *c*

Figure 6: 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.

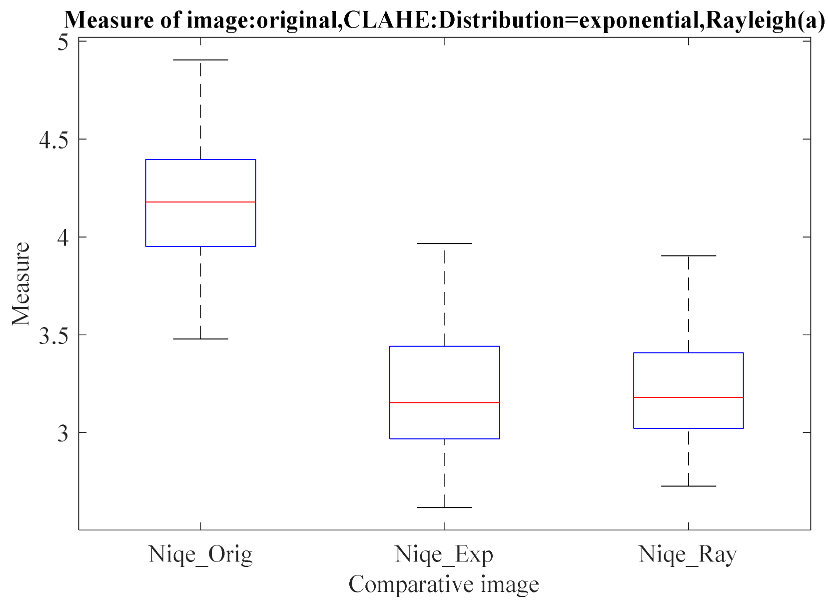
Table 2: Comparison of the values of non-reference estimates of the original image and transformed images by the CLAHE method when changing the values of the distribution and cliplimit parameters

№ Image	Evaluation of the original image		Distribution	NIQE Evaluation Options			Evaluation options BRISQUE		
	NIQE	BRISQUE		min NIQE	cliplimit for min NIQE	BRISQUE for min NIQE	min BRISQUE	cliplimit for min BRISQUE	NIQE for min BRISQUE
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	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 clip limit 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. 7, 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 boxplot.



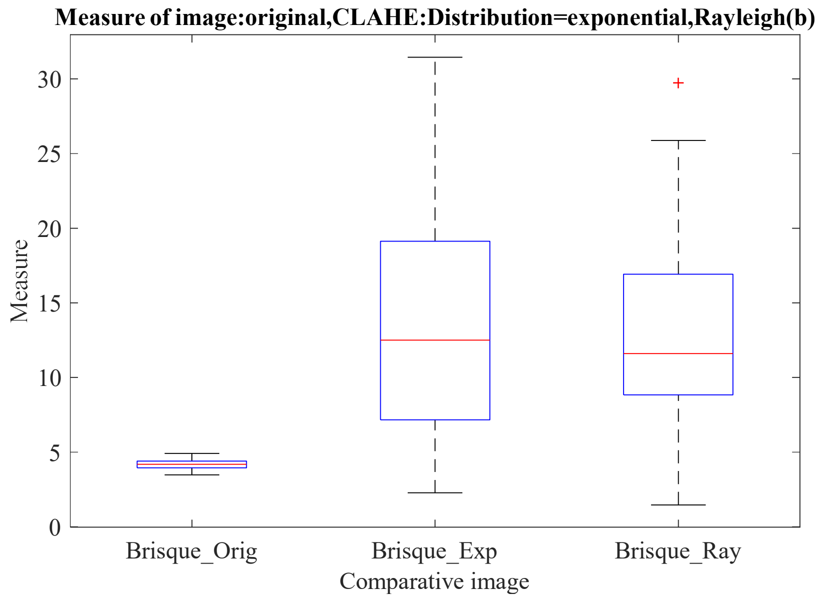


Figure 7: Comparison of original image with CLAHE (distribution method: 'exponential','rayleigh') transformation results: a - with minimum NIQE scores; b - with minimum BRISQUE scores

Fig. 7 shows the minima, maxima, medians, lower and upper quartiles of the NIQE (top) and BRISQUE (bottom) ratings. The box with a mustache in Fig. 7, *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. 7, *b* shows that the values of the BRISQUE score are increasing, which means that the quality of the images is deteriorating. Fig. 8 shows a box with a mustache for the clip limit parameter.

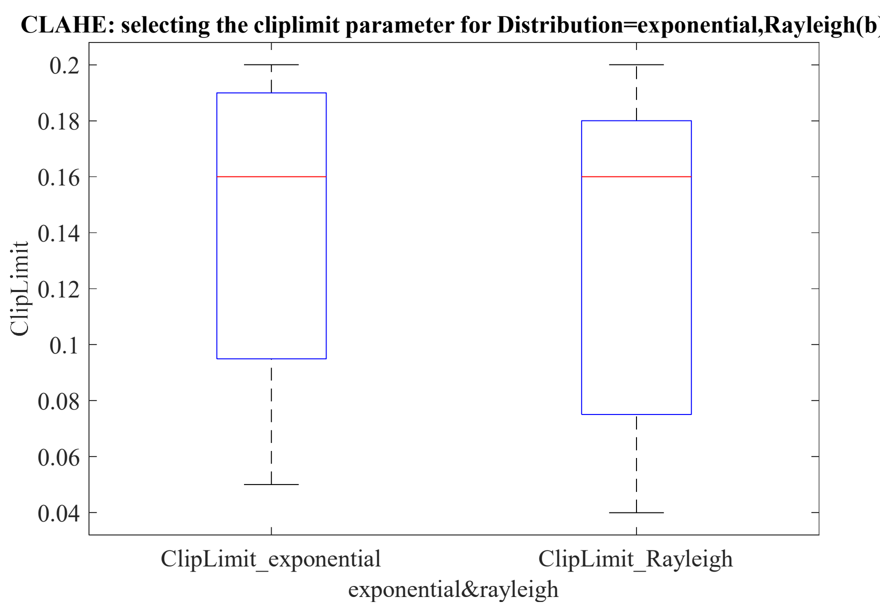


Figure 8: Selecting the values of the cliplimit parameter of the transformation by the CLAHE method with the distribution parameters equal to 'exponential' (left) and 'rayleigh' (right)

Boxplot in Fig.8 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[20].

6. DISCUSSION OF THE RESULTS OF THE STUDY OF METHODS FOR ENHANCE THE CONTRAST OF 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, 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. 7) 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. 8). 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 adaptive histogram equalization with limited contrast and the gamma correction method significantly increases the contrast of X-ray images. 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 [2-13] 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, 0.2] 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], γ), where $0.4 \le high\_in \le 0.7$, $0 \le \gamma \le 3$ 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], γ), where $0.4 \le low\_in \le 0.7$, $0 \le \gamma \le 3$

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. CONCLUSION

The study analyzes the possibilities methods of gamma correction and CLAHE to enhance the contrast of X-ray images. The analysis was carried out using non-reference estimates of Niqe and Brisque. 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 adaptive histogram equalization with contrast limited.

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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