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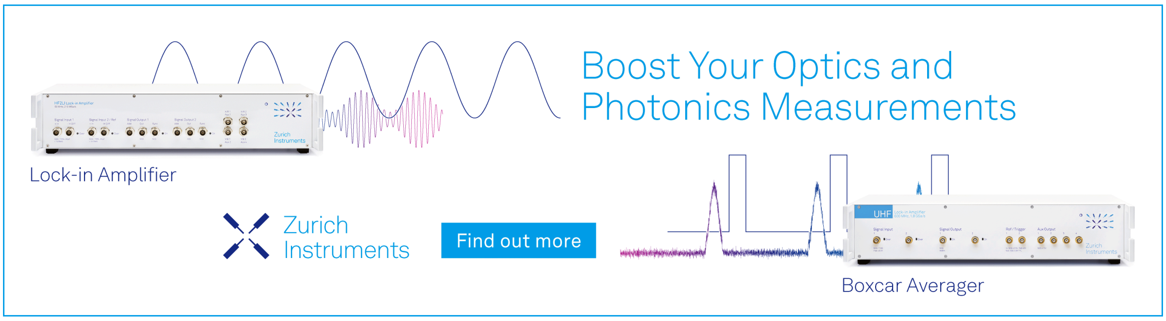

X-Ray Image Contrast Estimation and Enhancement Algorithms

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Abstract. In medicine, X-ray images are important, on the basis of which medical professionals can obtain necessary information about the internal structures of patients. The diagnosis is determined using the information that has been received. In some cases, it will not be possible to obtain information sufficient for diagnosis from X-ray image. For example, if the radiation is not delivered to the patient in sufficient quantity, the contrast of the medical X-ray image will not meet the requirement, which means that the analysis of the image will be complicated. This does not allow for making an accurate diagnosis. So, when fine-tuning the contrast of the X-ray image, it's important to guide the patient through the initial processing of the X-ray image, sparing them from undergoing a re-examination. The automation of this process requires the use of objective evaluation indicators. The primary objective of this research is to enhance the contrast of X-ray images through the utilization of an algorithm. Additionally, it aims to evaluate the resulting images using the widely recognized RMS (Root Mean Square) evaluation indicator. Furthermore, the research seeks to identify the most effective algorithm or sequence of algorithms based on this evaluation indicator.
Keywords. algorithm, contrast enhancement, CLAHE, contrast stretching, contrast enhancement, histogram, morphological evaluation, index,, no-reference evaluation, X-ray image.

INTRODUCTION

Presently, the integration of digital technologies is being extensively adopted within the medical domain [1]. Within this healthcare institution, the digital X-ray imaging equipment holds significant importance. Because medical experts cannot analyze human internal structures with a simple eye. Typically, this process relies on the X-ray image acquired through radiography of the patient [2]. In some cases, the X-ray image taken from the equipment does not have enough contrast to make a diagnosis [3]. In this case, the medical professional is required to re-X-ray the patient because the image does not provide complete and accurate information about the patient's abnormalities. In such a situation, the patient receives X-rays again, which harms his health. Therefore, the most appropriate solution is to carry out the diagnosis by passing the obtained X-ray image through the initial processing stage [4]. In the pre-processing step, all images are processed to automate image processing [5-8]. The problem of increasing image contrast during processing is relevant [9,10]. Because the most optimal method of contrast enhancement for X-ray images will be determined, using it will be possible to automate the process effectively.

Contrast in an X-ray image is the difference in brightness in the image of human internal structures and tissues. In most cases, the image contrast is low. In this case, contrast enhancement algorithms of the preliminary processing stage are used [11, 12].

The objective of this study is to identify the most effective contrast enhancement algorithm or combination of algorithms for X-ray images. This determination is based on a comprehensive analysis of existing literature and

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extensive experimentation. As the foundation for this research, we have considered algorithms such as histogram equalization [13-16], CLAHE (Contrast Limited Adaptive Histogram Equalization) [17-19], contrast stretching [18,20,21], and morphological contrast enhancement [22]. In this case, it is important to evaluate the output images generated by the application of algorithms. A subjective method among known image contrast evaluation methods is visual evaluation.

Visual evaluation of image contrast is a visual perception of the difference between light and dark areas in an image [23]. Nonetheless, automating the image processing procedure through this approach is not feasible. Because subjective evaluation requires a professional expert with strong knowledge. This in turn leads to spending a lot of time and money. That is why it is important to objectively evaluate image contrast in numerical values.

The criteria for objective evaluation of image contrast are divided into two categories, reference and no-reference. In the reference evaluation, two images, that is, the original image I_{et} with normal contrast in the objective evaluation and the original image with a reduced contrast I_{bad} of this original image are defined, and the image I_c after applying the contrast enhancement algorithm to the image is determined by some criterion B_2 comparison is made through in addition, if the two images are closer $I_{et} \sim I_c$, then the image contrast estimate $B_2(I_{et}, I_c) \to opt$ is assumed to be better.

In no-reference evaluation, based on only one image, its contrast is evaluated using a criterion $B_1(I_c)$. In numerous real-world scenarios, a reference image may not be accessible. Consequently, this research article delves into the examination of no-reference contrast evaluation criteria.

LITERATURE REVIEW

One of the earliest research studies in contrast evaluation is the Weber contrast. Following Weber's experiments, he held the belief that it was feasible to ascertain the limits of the eye's vision. He established the contrast of an image by considering the ratio between the brightness of an object and the brightness of its background. Therefore, in some literature, this contrast coefficient is called Weber's law [23]. However, since object and background detection from an image is a complex process, this evaluation is rarely used.

Michelson contrast is mainly determined by comparing dark and bright areas in an image, and it basically estimates the global contrast of an image. Modified versions of the Michelson contrast are detailed in [24]. Nevertheless, different circumstances within a given image, such as the presence of salt-and-pepper noise, can result in an exaggerated estimation of contrast, which may not align with the visual assessment of the image. Therefore, this indicator does not allow an accurate assessment of image contrast. In [24], various indicators for evaluating image contrast are introduced. One of these is the global contrast evaluation indicator called Haralick contrast. It's part of a set of texture descriptors derived from the GLCM (Gray-Level Co-occurrence Matrix), calculated from the brightness component of the digital image. Specifically, this contrast measurement considers only brief inter-pixel correlations.

A global contrast measure called global contrast factor (GCF) is described in [25], which somehow corresponds to a relatively wide range of subjective ratings of natural images with different contrasts [24].

The RMS (Root Mean Square) contrast, which relies on the standard deviation of image brightness, was introduced by Bex and Makous [26]. RMS estimates the global contrast, and its calculation algorithm is relatively simple and fast. This indicator has been demonstrated to be a dependable indicator for predicting the threshold of human contrast detection in natural environments [27]. The contrast enhancement methods calculated histogram equalization, CLAHE, LHE methods are fully analyzed in the research paper [28]. Contrast enhancement methods for brain MRI images were used in [29] and evaluated using the RMS indicator.

METHODS

Since the image is a two-dimensional function, the given input image is defined by $I_{org}(x, y)$, and the image contrast evaluation criterion is defined by B_1 as an operator. In light of the examination of existing literature, the RMS no-reference indicator was selected to evaluate the X-ray image contrast, namely:

$$B_1(I) = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(I_i - \bar{I}\right)^2},$$

where I_i – is the brightness in i-pixel, $\overline{I} = \frac{1}{n}\sum_{i=1}^{n} I_i$.

$I_{org}(x, y)$ affects the contrast enhancement of the original image as a certain algorithm A The resulting output image is $I_c(x, y)$, and the above contrast enhancement algorithms are defined as operators as follows (Table 1).

TABLE 1. Definition of contrast enhancement algorithms as an operator

Operator	Name of algorithm	Formula
A_1	Histogram equalization	$A_1\left(I_{org(x,y)}\right)$
A_2	CLAHE	$A_2\left(I_{org(x,y)}\right)$
A_3	Contrast stretching	$A_3\left(I_{org(x,y)}\right)$
A_4	Morphologic contrast enhancement	$A_4\left(I_{org(x,y)}\right)$
A_5	Histogram equalization+ CLAHE	$A_2\left(A_1\left(I_{org(x,y)}\right)\right)$
A_6	Histogram equalization+ Contrast stretching	$A_3\left(A_1\left(I_{org(x,y)}\right)\right)$
A_7	Histogram equalization+ Morphologic contrast enhancement	$A_4\left(A_1\left(I_{org(x,y)}\right)\right)$
A_8	CLAHE+Contrast stretching	$A_3\left(A_2\left(I_{org(x,y)}\right)\right)$
A_9	CLAHE+ Morphologic contrast enhancement	$A_4\left(A_2\left(I_{org(x,y)}\right)\right)$
A_{10}	Contrast stretching+ Morphologic contrast enhancement	$A_4\left(A_3\left(I_{org(x,y)}\right)\right)$

Histogram equalization—enhances the overall contrast of an image based on the redistribution of pixel intensities in the image histogram. CLAHE increases the contrast by redistributing the pixel intensities to the selected sub-areas of the image based on the contrast threshold. Contrast stretching involves modifying the image contrast by expanding the intensity values, utilizing the minimum and maximum values present in the image. Morphological contrast enhancement - enhances contrast while preserving image edges and details using mathematical morphological operations such as erosion and dilation. Below is the code of these algorithms written in the Python programming language:

A_1 – **Histogram equalization:**

```
equalized = cv2.equalizeHist(img)
```

A_2 – **CLAHE:**

```
clahe = cv2.createCLAHE(clipLimit=4, tileGridSize=(4, 4))
equalized = clahe.apply(img)
```

A_3 – **Contrast stretching:**

```
image_cs = np.zeros((image.shape[0],image.shape[1]),dtype = 'uint8')
min = np.min(image)
max = np.max(image)
for i in range(image.shape[0]):
  for j in range(image.shape[1]):
    image_cs[i,j] = 255*(image[i,j]-min)/(max-min)
```

A_4 – **Morphological contrast enhancement:**

```
kernel = cv2.getStructuringElement(cv2.MORPH_RECT, (5, 5))
closed = cv2.morphologyEx(img, cv2.MORPH_CLOSE, kernel)
gradient = cv2.morphologyEx(closed, cv2.MORPH_GRADIENT, kernel)
min_intensity = np.min(gradient)
max_intensity = np.max(gradient)
```

```
normalized = ((gradient - min_intensity) / (max_intensity - min_intensity)) * 255
normalized = normalized.astype(np.uint8)
img_enhanced = cv2.addWeighted(img, 4, normalized, 0, 0)
```

The process for determining the optimal contrast enhancement algorithm for X-ray images or the algorithm sequence involved the following steps:

1. The image is loaded: input $I_{org}(x,y)$
2. Compute $B_1\left(I_{org}(x,y)\right)$
3. $I_c^j = A_j\left(I_{org(x,y)}\right), j=\overline{1,10}$ contrast enhancement algorithms are introduced to the original image.
4. Compute $B_1\left(I_c^j(x,y)\right), j=\overline{1,10}$
5. If $B_1\left(I_{org}(x,y)\right) < B_1\left(I_c^j(x,y)\right), j=\overline{1,10}$ then "Image contrast enhancement method is good" else "Image contrast enhancement method is bad"
6. $optimal = \max_q\left\{\frac{1}{m}\sum_{k=1}^{m}\left|B_1^q\left(I_c(x,y)\right)-B_1^q\left(I_{org}(x,y)\right)\right|\right\}, q=\overline{1,10}$, $m-$ the number of X-ray images.
7. A_q is an optimal algorithm and $\{B_1, A_q\}$ is an optimal pair.

RESULTS

In the computational experiment, 215 x-ray image samples from the kaggle image database were used [30]. Contrast enhancement algorithms calculated histogram equalization, CLAHE, contrast stretching and morphological contrast enhancement algorithms and their various sequences were applied to the images. The resulting images were evaluated using the RMS evaluation indicator. One sample of the evaluated images and its histogram, the number of images satisfying the condition $B_1\left(I_{org}(x,y)\right) < B_1\left(I_c(x,y)\right)$ are presented in Table 2.

Based on the findings presented in Table 2-3, it was observed that the morphological contrast enhancement algorithm and sequences incorporating this algorithm tend to overestimate the contrast of X-ray images. Therefore, these algorithms cannot be the optimal algorithm for X-ray image contrast enhancement. The selection of the most optimal algorithm from $A_1, A_2, A_3, A_5, A_6, A_8$ was performed by considering their $B_1\left(A\left(I_{org}\right)\right)$ values.

The following results were obtained from Table 4 for the RMS index for X-ray images in the base: out of 215 images, 2 in the A_1 algorithm, none in the A_2 algorithm, 1 in the A_3 algorithm, and 209 in the A_5 algorithm, A_6 and 3 images in A_8 showed the highest RMS values. Based on the obtained results, the A_5 algorithm can be accepted as the most suitable algorithm.

The following results were obtained for the image RMS index values obtained using histogram equalization, CLAHE and contrast stretching algorithm for the base images obtained: RMS index of 211 images in algorithm A_1 , 3 in A_2, 1 in A_3 out of 215 images received the highest values. When considering the individual algorithms on their own, it was determined that A_1 performed the best.

To automate contrast enhancement during the pre-processing of images using algorithms A_5 , A_1 , it is crucial to establish the RMS value range of the original image. Based on the earlier results, it was discerned that the effectiveness of algorithms A_5 , A_1 is notable when the RMS value of the original image falls within the range of $[13-18]$.

CONCLUSION

Enhancing the quality of X-ray images through contrast enhancement algorithms holds the promise of enhancing the accuracy and reliability of medical diagnosis and treatment procedures.

In this research, X-ray image contrast was modified using histogram equalization, CLAHE, contrast stretching and morphological contrast enhancement algorithms and their different sequences. Images resulting from these algorithms were evaluated using the popular RMS indicator. As a result of conducting this research, the following results were obtained:

- according to the highest RMS values, it was established that the optimal algorithm A_1 is indeed the histogram equalization algorithm;

- X-ray image contrast enhancement was checked by applying different sequence of 4 obtained algorithms. In conclusion, it was determined that the morphological contrast enhancement algorithm and the algorithms used in combination with it did not meet the specified criteria. Among these combinations, it was found that the optimal algorithm is A_5 , which involves a sequence of histogram equalization and CLAHE algorithms.

- to automate image contrast enhancement, it was decided to use A_5 algorithm if RMS value is in the range [13-18], otherwise not to change image contrast.

TABLE 2. Original image and images obtained from contrast enhancement algorithms, their histograms, images satisfying the condition $B_1\left(I_{org}(x,y)\right) < B_1\left(I_c(x,y)\right)$

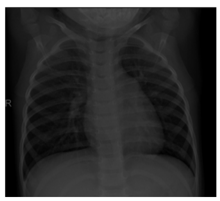
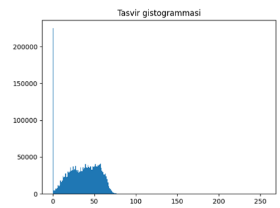
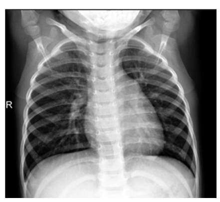
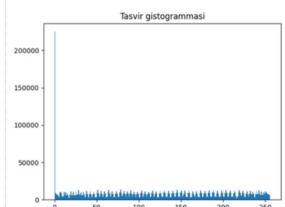
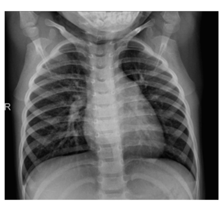
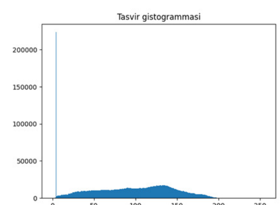
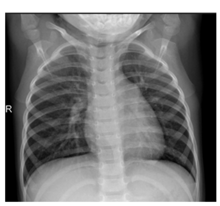
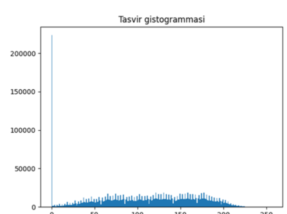
Image name	Image	Histogram	The number of images satisfying the condition $B_1\left(I_{org}(x,y)\right) < B_1\left(I_c(x,y)\right)$
Original image			-
Histogram equalization			213
CLAHE			209
Contrast stretching			215

TABLE 3. Original image and images obtained from contrast enhancement algorithms, their histograms

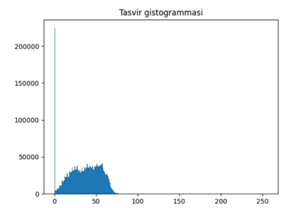
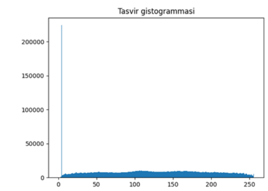
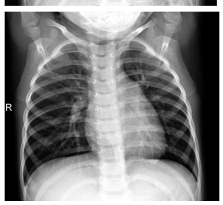
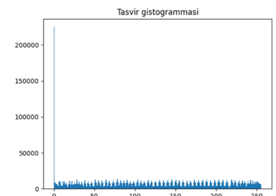
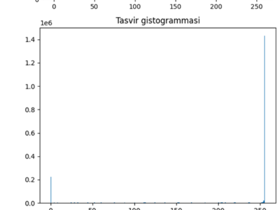
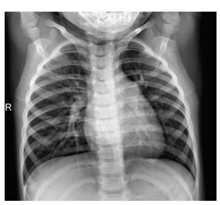
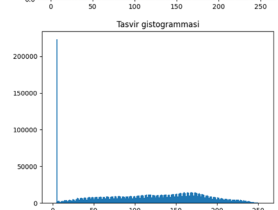
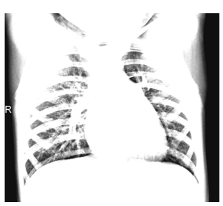
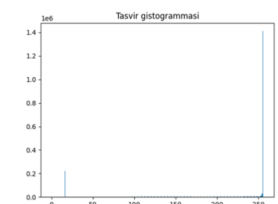
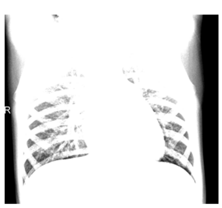
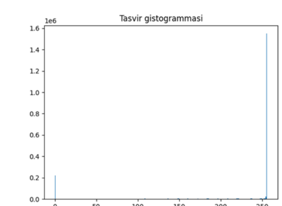
Image name	**Image**	**Histogram**	**The number of images satisfying the condition** $B_1\left(I_{org}(x,y)\right) < B_1\left(I_c(x,y)\right)$
Original image			-
Histogram equalization+ CLAHE			213
Histogram equalization+ Contrast stretching			213
Histogram equalization+ Morphological contrast enhancement			213
CLAHE+Contras t stretching			209
CLAHE+ Morphological contrast enhancement			209
Contrast stretching+ Morphological contrast enhancement			215

TABLE 4. Contrast enhancement algorithms $B_1(A(I_{org}))$ values

Image name	$B_1(A(I_{org}))$ values							Algorithm number with highest $B_1(A(I_{org}))$ value
	Original	A_1	A_2	A_3	A_5	A_6	A_8	
Image1	23.25	73.51	57.45	72.25	73.52	73.50	57.45	5
Image17	19.72	80.18	51.72	61.25	80.29	80.15	51.72	5
Image64	16.95	73.98	44.87	54.01	73.96	73.95	44.87	1
Image84	68.34	73.89	72.71	69.03	73.91	73.85	72.72	5
Image105	78.48	68.72	79.81	78.49	68.72	68.72	79.86	8
Image134	49.49	73.96	69.48	49.50	73.97	73.96	69.49	5
Image158	64.66	73.23	67.56	64.67	73.33	73.29	67.57	5
Image167	52.25	73.89	72.06	53.28	73.94	73.91	72.07	5
Image207	79.51	69.45	77.93	79.52	69.45	69.45	77.94	3
Image209	68.68	74.12	70.90	68.69	74.13	74.10	70.91	5
…	…	…	…	…	…	…	…	...

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