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Non-Complex Statistics-Driven Algorithm for Enhancement of Grayscale and Color Images

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Abstract

Low-contrast images are viewed with obscured details and are unfavorable to the observer. Hence, it is a necessity to process such an effect efficiently to get images with lucid details as the need for clear images become a global demand. Therefore, a statistics-based algorithm of simple complexity is introduced in this research to process color and grayscale images with low contrast. The proposed algorithm consists of five stages, where the first and second stages include the use of two different statistical s-curve transformations, the third stage combines the outputs of the aforesaid stage, the fourth stage improves the brightness, and the fifth stage reallocates the pixels to the natural interval. The proposed algorithm is compared with six modern algorithms, and the outputs are evaluated using two no-reference methods. The obtained results show that the proposed algorithm performed the best, providing the highest image evaluation readings and it was the fastest among the comparison methods.

Keywords:
Contrast enhancement, Color image, Grayscale image, Hyperbolic tangent, Kumaraswamy distribution, Logistic distribution, Normalization; Pătraşcu model.

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I. INTRODUCTION

Digital images are deemed the most significant way of capturing and displaying information [1], and for that, various mechanisms have been utilized to save, process, and capture such images [2]. However, the captured images are usually obtained with degradations, and they do not signify the original view [3]. One of these degradations that always occur in an image is the low-contrast effect [4]. The low-contrast effect can occur due to poor lighting conditions, incorrect camera settings, or weather conditions. To filter such low-contrast images, a contrast enhancement (CE) technique is commonly implemented [5]. Contrast is the difference between the highest and the lowest pixel values in an image. If the difference is small, the contrast is low, and vice versa. If the contrast is high, the image details are perceived better, and the colors appear natural [6]. Contrast is an important factor in any assessment of image quality in image processing [7]. The following Figure 1 shows the difference between a good-contrast image and a low-contrast image for both grayscale and color images.

CE is a technique that improves the visible quality and features of an image by making it clearer to be viewed by the observer or utilized by a task. CE can be done in the spatial or frequency domain. The spatial domain methods focus on direct pixels modification, while the frequency domain methods focus on transforming the image to the frequency domain, applying the manipulations then transforming the image back to the frequency domain [8]. CE techniques are different, and they utilize various concepts. Some are simple and others are complicated. This depends on the utilized concept and the involved computations. Some CE concepts are histogram equalization, Retinex, fuzzy, type-II fuzzy, artificial intelligence-based, statistics-based, and so forth [9]. Digital images have become extremely important and irreplaceable in many areas such as surveillance, public identity verification, criminal justice systems, military applications, scientific, medical, and so forth.

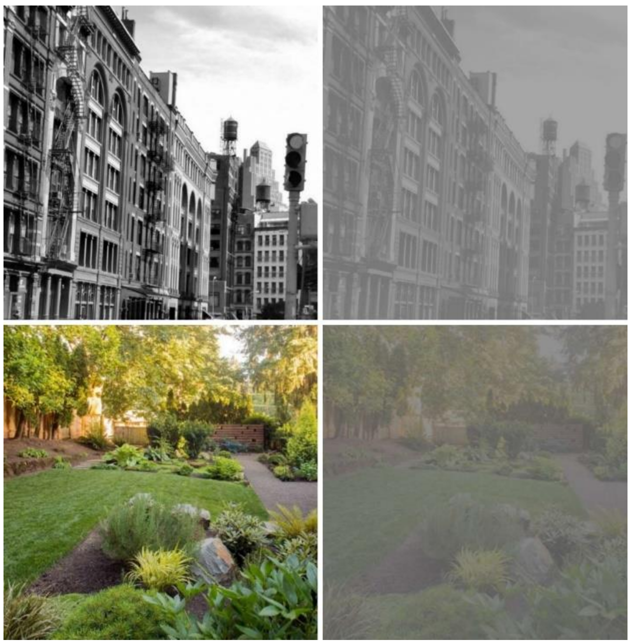

Fig. 1. Good-contrast and low-contrast grayscale and color images (pexels.com).

This requires the images to be of good contrast to distinguish their details properly. That's why CE techniques are needed to filter such low-contrast images [10]. Based on the mentioned facts, a non-complex statistical-based algorithm is developed in this research to process the contrast of color and grayscale images. The developed algorithm of five different stages, for which every stage provides a significant contribution to the CE process. Furthermore, adjusting the contrast is managed using one parameter. The main objectives of this research are to create a non-complex algorithm for CE and to deliver a fast-processing approach for various contrast-degraded grayscale and color images. The algorithm is tested with various real-contrast degraded images and compared with various algorithms. Finally, comparisons are made with different methods and two well-known image evaluation methods are used to assess the quality of results. The rest of this research is arranged as follows: Section II reviews some of the related works related to CE; Section III explains the proposed algorithm. Section IV delivers the results and their discussion; Section V provides the important conclusions.

II. RELATED WORK

Many CE techniques have been created, developed, or amended by different researchers. In [11], the authors have proposed a kernel-based retinex (KBR) approach. It begins with performing the retinex computations. Next, a resetting mechanism is utilized followed by applying a specialized function for non-linear scaling. Finally, the scaled intensities are averaged to produce the output. The authors of [12] proposed an algorithm named brightness preserving dynamic fuzzy histogram equalization (BPDHE), which begins by calculating the fuzzy histogram of the input image to be partitioned into several sub-histograms. Next, a dynamic equalization approach is applied to each histogram. Finally, the brightness of the resulting image is normalized to produce the output.

In [13], the authors created a contextual variational CE approach. It begins by creating a 2D histogram from the image by utilizing the relationship between the pixel and its adjacent pixels. The new histogram is obtained by utilizing the minimized Frobenius norms and another uniform histogram. The output image is attained using a specialized mapping process between the diagonal elements of the old and new histograms. In [14], a fusion-based CE algorithm is developed. It begins by performing local enhancement on the input image. Then, it performs global enhancement on the input image. Next, both outputs are fused using a multi-resolution Laplacian pyramid-based approach to produce the output.

Moreover, a non-parametric modified histogram equalization (NMHE) approach is developed by Poddar et al. [15], which begins by inputting the image and then determining its histogram and its clipped version. Next, two measures are obtained which are spike-free histogram and un-equalization. These measures are used to modify the histogram of the input image aided by a unique alteration function. In addition, another CE approach is introduced in [16] with the name of median mean-based sub-image clipped histogram equalization (MMSICHE). It starts by determining the mean and median rates of the input. The next step involves the use of a plateau limit to clip the histogram. Then, the clipped histogram is splatted, and each part is filtered with histogram equalization depending on the predetermined values. To get the result, all filtered parts are joined together.

In [17], an algorithm named recursively separated exposure sub-image histogram equalization (RSESIHE) was introduced. It works by recursively dividing the histogram. Next, each separated histogram is equalized depending on its exposure threshold. The divided portions are then combined to form the output image. Singh et al. [18] introduced two algorithms which are edge-based texture histogram equalization (ETHE) and dominant orientation-based texture histogram equalization (DOTHE). The ETHE begins by determining the important image edges. Then, it creates the histogram by utilizing the gray levels that are found around the edges. Finally, it modifies the histogram based on a distinct transfer function. The DOTHE starts by partitioning the image into two types of patches which are rough and smooth. The rough ones are again partitioned into non-dominant and dominant. The histogram of the dominant patches is created, and a special processing function is used to modify the intensities and produce the output image.

In [19], the author created a CE approach based on intrinsic decomposition. It begins by decomposing the image into its illumination and reflectance components. The reflectance is regularized by using a weighted $\ell 1$ norm and the illumination part is regularized by using a piecewise constraint. Then, a Split Bregman approach is applied to get the output. In [20], the authors developed a gamma correction-based algorithm. It begins by checking the image if it is bright or dim using a specialized mechanism. If it is bright, the negative of the image is taken, adaptive gamma correction is applied, and a negative reversal is applied to get the output. If it is dim, the image is filtered by a truncated cumulative distribution method then the adaptive gamma correction step is applied to get the output.

In [21], the authors propose a CE method that starts with obtaining the wavelets of the input image. Then, it implements an optimum gamma adjustment procedure to maintain the appearance while improving the contrast. In [22], the author introduced a CE approach that utilizes a logarithmic law to modify the histogram. It begins by converting the input image from the RGB domain to the YCbCr domain. The Y layer is modified by taking its histogram. Then, an addition-based modification is applied followed by a logarithmic-based modification method to modify its intensities. Next, the output is filtered by histogram equalization for global enhancement followed by the application of a discrete cosine transform-based approach for local details enhancement. The image is transformed back to the RGB domain, and the output of this algorithm is obtained.

In [23], the authors developed an algorithm that depends on statistical discriminative co-occurrence. It begins by estimating the reflectance of the input image, then from this reflectance, a 2D histogram is computed. Next, the 2D histogram is utilized by a specialized approach to modify the contrast. The output of this step is sent to a newly designed mapping function to produce the final output. From the reviewed approaches, it can be seen the CE can be implemented using different concepts. Some are recursive, some are iterative, some involve a lot of calculations, and others do not produce the desired results. Based on these observations, the opportunity is still available to create an algorithm that owns a simple structure and can deliver adequate quality results in a fast way.

IIII. PROPOSED ALGORITHM

In this study, the developed algorithm is created based on a combination of statistical and image processing concepts, in that it includes various equations that each contribute distinctly to producing the desired results. Furthermore, the main motivation behind creating this algorithm was to high-quality outcomes in a fast manner without introducing any processing artifacts. The field of contrast enhancement is open to various statistical s-curve approaches that can modify the contrast [24, 25]. Moreover, appropriate logarithmic image processing (LIP) models can be utilized to mix the features of any given two images, in that many of these models are available and have been utilized in various image processing fields [26-28]. Once the features are mixed, additional processing must be applied to generate the resulting image. By utilizing such notions, the proposed algorithm is created. Figure 2 demonstrates the diagram of the developed algorithm. To begin with, the input image is filtered by two s-curve approaches distinctly to modify the contrast. Next, the outputs of these two steps are mixed using a suitable LIP model. Next, the brightness is improved using another statistical method. Lastly, the conventional normalization function is utilized to redistribute the image pixels to the regular interval.

As a thorough explanation, the low-contrast image is initially filtered using the cumulative distribution function of the Kumaraswamy distribution (CDFKD) approach, in that it is deemed a curvy transform approach that can modify the image contrast. The equation of the CDFKD approach can be written as follows [29]:

$$K_{(x,y)} = 1 - \left(1 - \left(I_{(x,y)}\right)^{\alpha}\right) \quad (1)$$

where α and β are two constants that control the curve of the CDFKD, in that for this study, ($\alpha > 0$) with higher values yield more contrast enhancement. x and y are image coordinates; $K_{(x,y)}$ is the resulting image from the CDFKD approach; $I_{(x,y)}$ is the input image with contrast distortion. After that, the image $I_{(x,y)}$ is filtered for the second time using the probability density function of the logistic distribution (PDFLD) approach. This approach is also a curvy transform that changes the image contrast. The equation of the PDFLD approach can be written as follows [30]:

$$L_{(x,y)} = \frac{\exp\left(-I_{(x,y)}\right)}{\left(1 + \exp\left(-I_{(x,y)}\right)\right)^2} \quad (2)$$

where $L_{(x,y)}$ is the resulting image of the PDFLD approach. Now, two contrast-modified images are obtained. Therefore, the features of these two images are combined using an adequate LIP model. Many LIP models are available, yet a simple and efficient one must be utilized. Hence, different models have been tested for this study, and the Pătraşcu model is selected due to its suitability, simplicity, and effectiveness. The equation of the Pătraşcu model can be written as follows [31]:

$$P_{(x,y)} = \frac{\left(K_{(x,y)} + L_{(x,y)}\right)}{\left(1 + \left(K_{(x,y)} \cdot L_{(x,y)}\right)\right)} \quad (3)$$

where $P_{(x,y)}$ is the resulting image from the Pătraşcu model; ($\cdot$) is a multiplication process. The output image at this stage requires some brightness enhancement. Therefore, a hyperbolic tangent (HT) function is applied for this purpose, and its equation can be written as follows [32]:

$$H_{(x,y)} = \frac{\left(\exp\left(P_{(x,y)}\right) - \exp\left(-P_{(x,y)}\right)\right)}{\left(\exp\left(P_{(x,y)}\right) + \exp\left(-P_{(x,y)}\right)\right)} \quad (4)$$

where $H_{(x,y)}$ is the resulting image from the HT function. One remaining issue is that the image pixels are not allocated to the full range. Thus, the classical normalization method is used to reallocate the intensities to the full range. The equation of the classical normalization method can be written as follows [33]:

$$N_{(x,y)} = \frac{\left(H_{(x,y)} - \min\left(H_{(x,y)}\right)\right)}{\left(\max\left(H_{(x,y)}\right) - \min\left(H_{(x,y)}\right)\right)} \quad (5)$$

where *min* and *max* are the lowest and highest pixel values; $H_{(x,y)}$ is the algorithm output. Lastly, the value of (α) must be set by the operator manually to get the desired outcome.

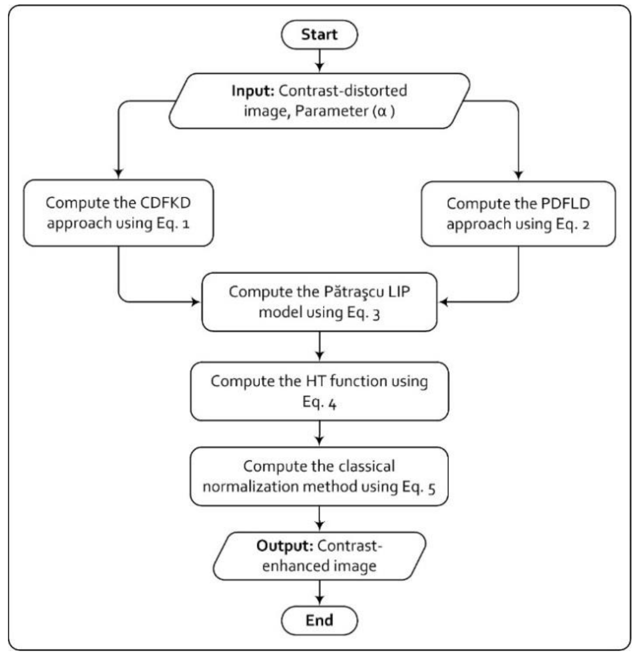

Fig. 2. The diagram of the proposed algorithm.

IV. RESULTS AND DISCUSSION

In this research, all the related information of the implemented experiments and comparisons is given. Different low-contrast gray and color images were used. These images were collected from different websites for free. More than one hundred images were collected to be used for experimental and comparison purposes. These images have different sizes and different contrast distortions. Yet, all of them have the type of (JPG). Moreover, the proposed algorithm is compared against six modern algorithms that have already been explained in the literature review. The comparison algorithms are (BPDFHE): brightness preserving dynamic fuzzy histogram equalization, (NMHE): non-parametric modified histogram equalization, (MMSICHE): median means-based sub-image clipped histogram equalization, (RESIHE): recursive exposure-based sub-image histogram equalization, (DOTHE): dominant orientation-based texture histogram equalization, and (ETHE): edge-based texture histogram equalization. These algorithms are implemented as the source codes are published by their authors.

There are many means used to measure the quality of the image, and each method has an algorithm based on a type or attribute related to the composition of the image. Therefore, two no-reference methods have been chosen to measure the quality of images, since no-reference (NR) methods do not require information on the reference image, which makes them highly desirable [34]. The first method used is (NSS), which means natural scene statistics [35]. It depends on the features of the moment and entropy in building the NSS model and using a database of large-sized images. The degree of deviation from the NSS models of distorted or low-contrast images is what makes them unnatural and reduces the statistical regularity of natural images. Thus, it is considered a reliable feature in assessing quality, since the NSS method was designed to capture statistical characteristics. Predicting the score and setting the probability feature for perceived quality is done using vector regression support. The outputs are grouped using distinct measures to obtain the final score.

The second method used to measure image quality is (BPRI), which means blind pseudo reference image [36]. The similarity between pseudo reference image (PRI) and anamorphic structures is calculated through PRI-based metrics. Therefore, similarity with the corresponding PRI depends on the intensity of the image distortion. The measures of different distortions are integrated based on PRI into the blind image quality assessment method using specialized methods. The outputs are grouped using distinct measures to obtain the final score. The NSS measures the quality of an image based on its contrast adequacy, while the BPRI measures the quality depending on the intensity naturalness. For both the NSS and BPRI, the input is only one image, and the output is a numerical value. If higher values are given, this means that the quality is better.

The proposed and comparative algorithms were implemented using the MATLAB 2018a programming environment with a processor Core i5-2400M 2.50 GHz and 4 GB memory. The proposed algorithm and the comparison methods, the image evaluation methods, and runtime measurements are all achieved under that environment. The experimental results include many grayscale and color images that are processed by the proposed algorithm to show its processing efficiency. Moreover, some real contrast distorted images are selected and processed using the proposed and the comparison methods, and their results are saved as images, and the runtimes are recorded. Next, all the saved images are gathered and inputted to each image evaluation metric separately to record the accuracy. After recording the accuracy for all images, the average performances are computed for each method and added to determine which method is the best in terms of metrics and runtime. Finally, the average performances are copied to Microsoft Excel to generate the graphical charts. The experimental results are demonstrated in Figures 3 to 8. The comparison outcomes are displayed in Figures 9 to 12. The scores of the utilized image evaluation methods are provided in Table 1. The graphical charts of the average performances are given in Figures 13 to 15.

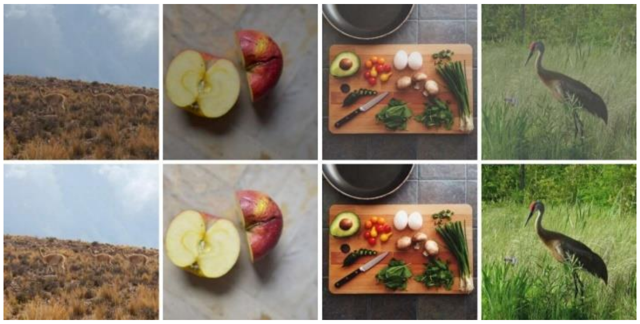

Fig. 3. Processing color images with natural contrast distortions (Batch -1-): (1st row) original images; (2nd row) results obtained by the proposed algorithm with *a* = (1.1, 1.5, 1.5, 1.8).

Fig. 4. Processing color images with natural contrast distortions (Batch -2-): (1st row) original images; (2nd row) results obtained by the proposed algorithm with *a* = (0.7, 1.2, 2.1, 2.5).

Fig. 5. Processing color images with natural contrast distortions (Batch -3-): (1st row) original images; (2nd row) results obtained by the proposed algorithm with *a* = (2, 2, 2.4, 2.5).

From the resulting images in Figure 3 to Figure 8, the output images which are filtered by the proposed algorithm are observed way better than their original observations according to different aspects. Accordingly, the colors have become clearer and brighter, the brightness is well-preserved from being augmented, and the contrast is increased to seem natural to the viewer. As for the provided histograms for every image, they support the findings, since the histograms of the filtered images illustrate an improved intensity distribution than those of the original images that are restricted to certain ranges, which is a true indication that these images own unacceptable visual quality. Figures 9 to 15 and Table 1 reveal the outcomes of comparisons in different aspects using different real degraded images, contrast enhancement algorithms, and accuracy evaluation methods. The BPDFHE method showed a slight change in contrast and an increase in brightness. Therefore, it recorded low with BPRI and above average with NSS, while being the second-fastest method according to the average runtime.

Fig. 6. Processing grayscale images with natural contrast distortions (Batch -1-): (1st row) original images; (2nd row) results obtained by the proposed algorithm with *a* = (1.1, 1.1, 1.7, 1.8).

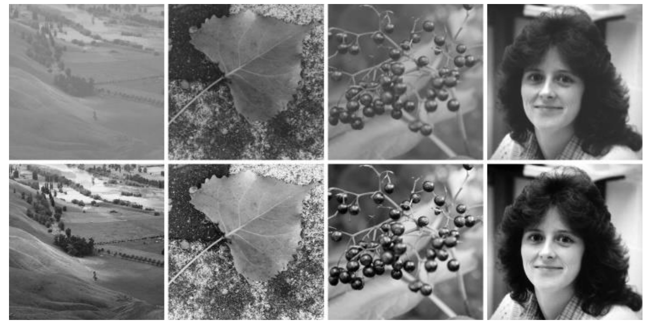

Fig. 7. Processing grayscale images with natural contrast distortions (Batch -2-): (1st row) original images; (2nd row) results obtained by the proposed algorithm with *a* = (0.8, 0.9, 0.9, 1.2).

Fig. 8. Processing grayscale images with natural contrast distortions (Batch -3-): (1st row) original images; (2nd row) results obtained by the proposed algorithm with *a* = (0.8, 0.8, 0.9, 0.9).

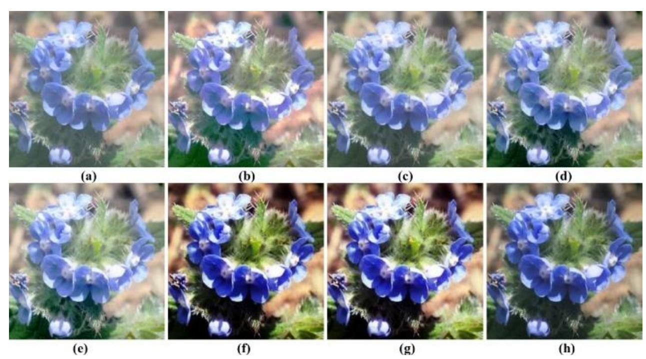

Fig. 9. The comparison results with real contrast-distorted color images (Batch -1-). (a) degraded image; other images are retrieved with: (b) BPDFHE; (c) NMHE; (d) MMSICHE; (e) RSESIHE; (f) ETHE; (g) DOTHE; (h) Proposed algorithm.

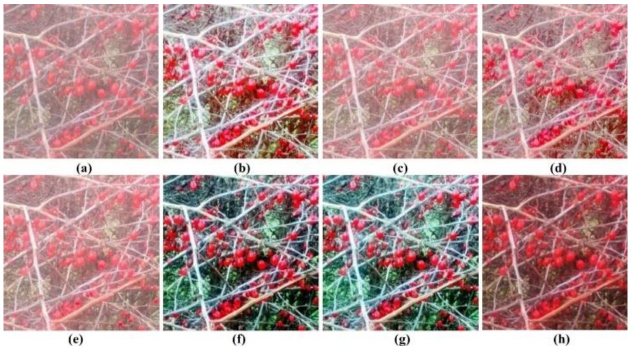

Fig. 10. The comparison results with real contrast-distorted color images (Batch -2-). (a) degraded image; other images are retrieved with: (b) BPDFHE; (c) NMHE; (d) MMSICHE; (e) RSESIHE; (f) ETHE; (g) DOTHE; (h) Proposed algorithm.

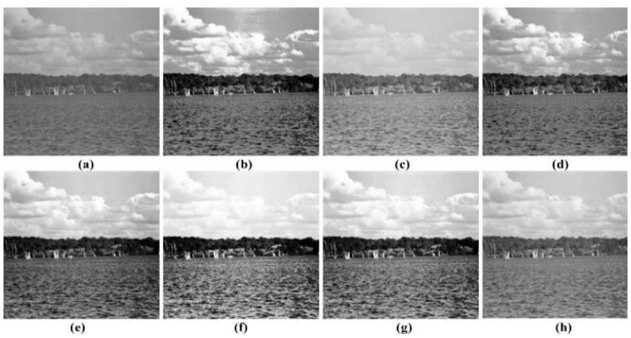

Fig. 11. The comparison results with real contrast-distorted grayscale images (Batch -1-). (a) degraded image; other images are retrieved with: (b) BPDFHE; (c) NMHE; (d) MMSICHE; (e) RSESIHE; (f) ETHE; (g) DOTHE; (h) Proposed algorithm.

The NMHE results showed a minor increased brightness with a touch of contrast enhancement. Therefore, it recorded high with BPRI and below average with NSS, while being the third fastest method according to the average runtime. The MMSICHE provided some minor distortions to the color images, a visible brightness increment in certain areas, and acceptable contrast. Therefore, it recorded low with BPRI, and high with NSS, being the sixth fastest method according to the average runtime .As for RSESIHE, it did not work well for color images and its performance was better with the grayscale images. Therefore, it recorded above average with BPRI, and average with NSS, being the slowest method in the comparison. As for the ETHE method, it altered the colors of the color images when processing the contrast yet performed well with the grayscale images. The colors were not very well displayed with increased brightness and moderate contrast. Therefore, it recorded below average with BPRI, and low with NSS, being the fourth-fastest method according to the average runtime. Moreover, the DOTHE acted very much like ETHE, having somewhat unnatural colors with increased brightness. Therefore, it recorded moderately with BPRI and lowest with NSS, being the fifth-fastest method according to the average runtime. As for the proposed algorithm, it delivered the best performances objectively and subjectively, as it provided the highest readings with BPRI and NSS while being the fastest among the comparison methods.

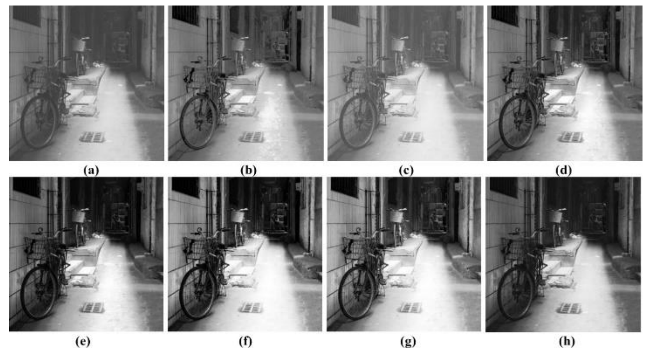

Fig. 12. The comparison results with real contrast-distorted grayscale images (Batch -2-). (a) degraded image; other images are retrieved with: (b) BPDFHE; (c) NMHE; (d) MMSICHE; (e) RSESIHE; (f) ETHE; (g) DOTHE; (h) Proposed algorithm.

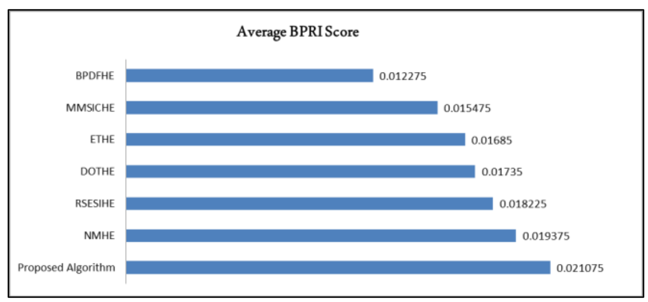

Fig. 13. The graphs of the average BPRI scores in Table 1.

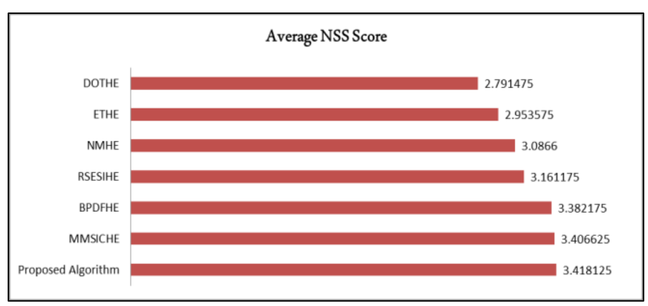

Fig. 14. The graphs of the average NSS scores in Table 1.

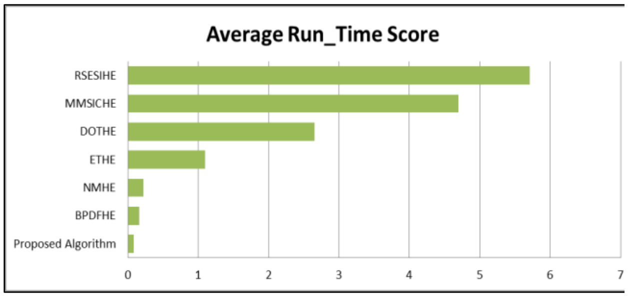

Fig. 15. The graphs of the average runtimes in Table 1.

Table 1. The scores of image evaluations and algorithms runtimes of the comparisons.

Method	Figure	BPRI	NSS	Time
Degraded	Fig 9	0.0226	3.206	N/A
	Fig 10	-0.0014	2.5468	N/A
	Fig 11	0.0096	2.8425	N/A
	Fig 12	-0.0115	3.1084	N/A
	Average	0.004825	2.925925	N/A
BPDFHE	Fig 9	0.0293	3.4439	0.180798
	Fig 10	0.0031	3.3797	0.184771
	Fig 11	0.0104	3.256	0.119743
	Fig 12	0.0063	3.4491	0.1446
	Average	0.012275	3.382175	0.157478
NMHE	Fig 9	0.041	3.4433	0.537801
	Fig 10	0.0148	2.8042	0.168428
	Fig 11	0.0129	2.7767	0.09872
	Fig 12	0.0088	3.3222	0.0915
	Average	0.019375	3.0866	0.22411225
MMSICHE	Fig 9	0.0352	3.4913	10.107181
	Fig 10	0.0066	3.45	7.601775
	Fig 11	0.0142	3.4794	0.571481
	Fig 12	0.0059	3.2058	0.52028
	Average	0.015475	3.406625	4.70017925
RSESIHE	Fig 9	0.0371	3.4654	13.297903
	Fig 10	0.0142	2.8639	9.136701
	Fig 11	0.0132	3.2263	0.215239
	Fig 12	0.0084	3.0891	0.208804
	Average	0.018225	3.161175	5.71466175
ETHE	Fig 9	0.0447	2.6844	1.898659
	Fig 10	0.0075	2.7365	1.421036
	Fig 11	0.0081	3.4574	0.552869
	Fig 12	0.0071	2.936	0.534734
	Average	0.01685	2.953575	1.1018245
DOTHE	Fig 9	0.0446	2.6228	4.37099
	Fig 10	0.0079	2.77	3.73719
	Fig 11	0.0109	3.0511	1.244428
	Fig 12	0.006	2.722	1.251804
	Average	0.01735	2.791475	2.651103
Proposed Algorithm	Fig 9	0.0461	3.4279	0.139759
	Fig 10	0.0116	3.3261	0.119617
	Fig 11	0.0176	3.4684	0.038414
	Fig 12	0.009	3.4501	0.033084
	Average	**0.021075**	**3.418125**	**0.0827185**

Such readings are achieved because the output images have lucid colors, natural contrast, and well-preserved brightness, as well as they did not introduce any processing errors. Such findings have a noteworthy significance since visually pleasing results are obtained with an algorithm that utilizes only five stages. It is understood that creating a non-complex algorithm yet delivering adequate results is uneasy. However, this assignment is fulfilled successfully in this research as seen from the reached results.

V. CONCLUSION

In this study, a multi-step algorithm with a non-complex structure has been introduced to enhance the contrast of grayscale and color and grayscale images. The developed algorithm owns five distinct stages. The first two processing stages utilize specific forms of Kumaraswamy and logistic distributions to filter the input images and alter their contrast individually. Then, the output images of these two stages are mixed using the Pătraşcu addition model. Next, the hyperbolic tangent function is utilized to improve the image luminance. Finally, the standard normalization method is applied to redistribute the image intensities to the standard dynamic range. The dataset of images utilized in this research includes around one hundred grayscale and color images with all being natural contrast distorted. The reason for using such images is that they can truly show the actual filtering abilities of the proposed algorithm. In addition, a comparison with six advanced algorithms was made and the accuracy of results was evaluated with two complex methods, in that their performances varied, and they scored less than the proposed algorithm in different aspects. The attained results demonstrated that the proposed algorithm was the fastest and provided the finest performances objectively and subjectively. From its results, the important image details were preserved, the contrast is noticeably improved while preserving the brightness from being undesirably increased, and the colors were displayed properly. Such matters are important as only five stages were utilized yet the results are of high quality and produced rapidly.

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خوارزمية غير معقدة تعتمد على المبادئ الاحصائية لتحسين الصور الرمادية والملونة

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الخلاصة:

يتم عرض الصور منخفضة التباين بتفاصيل غامضة وتكون غير واضحة للمشاهد. وبالتالي، من الضروري معالجة هذا التأثير بكفاءة للحصول على صور ذات تفاصيل واضحة حيث أصبحت الحاجة إلى الصور الواضحة مطلبًا عالميًا. لذلك، تم تطوير خوارزمية مبنية على الإحصائيات ذات حسابات بسيطة في هذا البحث لمعالجة الصور الملونة والرمادية ذات التباين المنخفض. تتكون الخوارزمية المقترحة من خمس مراحل، حيث تتضمن المرحلتان الأولى والثانية استخدام تحويليين إحصائيين مختلفين بكل منحنى S، وتجمع المرحلة الثالثة بين مخرجات المرحلتين المذكورة سابقا، والمرحلة الرابعة تحسن السطوع، والمرحلة الخامسة تعيد توزيع قيم الصورة على النطاق الديناميكي الطبيعي. تمت مقارنة الخوارزمية المقترحة بستة خوارزميات حديثة، ويتم تقييم المخرجات باستخدام طريقتين متخصصتين. أظهرت النتائج المتحصل أن الخوارزمية المقترحة كانت الأفضل أداءً حيث قدمت أعلى قراءات قياس دقة وكانت الأسرع بين طرق المقارنة.

الكلمات المفتاحية: تحسين التباين، الصورة الملونة، الصورة ذات التدرج الرمادي، الظل الزائدي، توزيع كوماراسوامي، التوزيع اللوجستي، التطبيع، نموذج باتراشكو.