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HLIPSCS: A Rapid and Efficient Algorithm for Image Contrast Enhancement

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Abstract: Contrast is an important feature in an image because the low-contrast effect causes poor details visibility, and the high-contrast effect leads to better-perceived details. The low-contrast effect happens due to many unavoidable reasons, and the demand for high-quality images entails the production of improved quality images. This obligates processing the low-contrast effect properly with an algorithm that works rapidly and preserves the essential image information. Many of the existing algorithms do not provide desirable results as they may amplify the brightness, deliver deficient colors, introduce insufficient contrast, or generate processing artifacts. Hence, a new HLIPSCS algorithm is introduced to avoid the aforesaid drawbacks and involves many processing concepts related to hyperbolic, logarithmic, and statistical approaches. It starts by applying two different hyperbolic methods, then their results are merged via an altered logarithmic approach. Next, statistical and contrast stretching approaches are applied to provide the anticipated outcome. The HLIPSCS algorithm is applied on different real contrast-degraded grayscale and color images, compared with eight different algorithms and the comparison outputs are evaluated using three different image evaluation methods. For the made comparisons and experiments, the HLIPSCS showed processing superiority as it delivered top performances in respect of image evaluation scores. Finally, the results of HLIPSCS have a way better appearance in the matters of brightness, contrast, and color representations.

Keywords: : HLIPSCS algorithm, Image enhancement, Contrast enhancement, Contrast stretching, Hyperbolic functions, Logarithmic image processing, Statistical methods

1. Introduction

Image Processing has undoubtedly become an increasingly researched field in computer science. Its revolution and development have grown rapidly, and benefits can be witnessed through its application across a myriad of other areas such as health, forensics, photography, biology, astronomy, and so forth [1]. Digital images in all their types are widely used across a plethora of fields and these images emerge from different kinds of devices, varying in precision levels [2]. Image enhancement aids in improving image accuracy and hence helps in different research fields [3]. Due to various circumstances related to the quality of the camera, its settings, surrounding environment, such as light and darkness, and insufficient experience of the operator, the image will be affected especially with regards to contrast and other degradations [4]. Low contrast is a common effect that happens in different imaging devices. To resolve it, approaches related to contrast enhancement (CE) are employed to improve the visible quality [5].

CE is a technique utilized to enhance the appearance of images, so they become more adaptable to human vision [6]. CE often comprises a set of operations such as increasing the differences between the foreground object and its background [7]. The field of enhancement is important for both computer vision and human perception alike in that the operations included within CE can improve brightness characteristics and/or the contrast of an image to intensify details and make them easier to perceive [8]. CE is widespread in its utilization across various applications and fields, including medical imaging, video surveillance systems, satellite image investigation, remote sensing, biology, geographical science, and so forth [9]. In CE, many algorithms aim at addressing improvable characteristics in an image such as uniform contrast, brightness preservation, noise tolerance, and color representation.

Additionally, these algorithms should be easy to implement with minimal inputs and exhibit appropriate noise suppression [10]. CE also refers to the rate of intensity variation that exists between different elements in digital images [11]. It can help to clarify the image features by

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taking advantage of the color presented on the display devices. Images with higher contrast levels usually appear clearer when related to lower contrast counterparts [12]. The low contrast phenomenon is a key quality degradation in digital images and is deemed an undesirable effect that should be processed efficiently. Therefore, various enhancement techniques have been introduced to achieve adequate enhancement [13]. Many CE algorithms have been developed and are categorized mainly as either spatial or transform domain. Histogram equalization, power-law transformations, logarithmic transformation, and statistical methods are famous spatial domain algorithms that are commonly utilized to ameliorate the contrast because of their rapidity and simplicity [14].

A wealth of algorithms has been introduced on CE throughout the past years, which range from simple to complex according to computations and concepts. In this study, a concise review of literature is made to identify the concepts of previous works, highlight the interesting points, and develop an algorithm that achieves better results. Lu et al. [15] provided an algorithm named adaptive increase in the value of histogram equalization (AIVHE). AIVHE changes the shape of the original PDF (i.e., probability density function) of the HE method to obtain a new PDF designed not to allow alterations in gray levels and allow gradual enhancement. Moreover, it utilizes tuning parameters to control the enhancement rate. Huang et al. [16] developed an adaptive gamma correction with weighting distribution (AGCWD) approach, where it combines the GC and HE methods. The authors used a cumulative distribution function (CDF) and employed a regulated gamma-based method to alter the transformed curve devoid of dropping the figures of the histogram. Additionally, a WD function is used to amend the histogram and reduce the production of unwanted artifacts.

Singh and Kapoor's [17] proposed a method so-called median-mean sub-image clipped histogram equalization (MMSICHE), in that it contains three key stages: the first being computing the mean and median values; the second being clipping and dividing the histogram; the third being the equalization of sub-histograms to create the output. Rahman et al. [18] introduced a dynamic stretching (DS) based algorithm, in that it uses the golden section search method to find a threshold so brightness can be preserved in the output image. Singh et al. [19] introduce a method known as recursive exposure sub-image histogram equalization (RESIHE), in that it performs ESIHE on an image till the exposure change in the succeeding iterations becomes lower than a predetermined threshold. In this algorithm, the histogram is partitioned into different smaller histograms depending on the threshold of the individual exposure. Next, the process of equalizing the histogram is applied to every small histogram. Excessive enhancement is avoided by performing histogram clipping in both approaches.

Jiang et al. [20] developed an optimal gamma correction and weighted sum (OGCWS) algorithm, in that it is aimed at amending the contrast and maintaining the average brightness close to the input image. However, the brightness amplification is somewhat related to the process of contrast enhancement, so they replaced the linear histogram equalization with a non-linear gamma correction scheme to avoid the brightness amplification effect and produce adequate contrast. Wong et al. [21] proposed a histogram equalization and optimal profile compression (HEOPC) algorithm, in that it commences by stretching the primary color channels of an image to provide an enriched color vividness. Then, it changes the primary colors to coupled human perceptual domains, followed by manipulating image intensity using an adapted HE technique compressing unwanted artifacts. This procedure restores color saturation to mitigate the loss of color. Parihar et al. [22] introduced a fuzzy contextual (FC) algorithm for color and grayscale images. The adopted algorithm heightens changes of intensity depending on the local relative information of the pristine image. A fuzzy dissimilarity histogram (FDH) is introduced to incorporate contextual information. Moreover, a transfer function that depends on the image intensity is also created from the FDH for contrast enhancement and a fuzzy-based procedure is developed to describe the adjacent characteristics of the image pixels.

Besides, Chen et al. [23] proposed an entropy-based mapping technique to solve both over and under enhancement effects by developing a linear model which produces a mapping curve that preserves the fine texture. The coefficient for this model is identified using turbulent particle swarm optimization. Consequently, another adaptive thresholding-based sub-histogram equalization method was introduced in [10], where it consists of three modules; the first is an adaptive thresholding-based histogram, which itself consists of two parts: optimum signal to noise ratio calculation and sharp adaptive multiple threshold selection. The second is histogram clipping, and the third is intensity transformation, which is responsible for retrieving each sub-image. Moreover, Veluchamy and Subramani [24] developed an algorithm that involves three steps. First, performing a color channel stretching for the red, green, blue (RGB) domain, and transforming it to the (HSI) domain, which stands for hue, saturation, intensity. Second, applying a new histogram weights allocation scheme depending on an improved gamma correction approach to the intensity channel. Third, converting the image back to the RGB domain to get the outcome. Likewise, a heuristic adaptive HE method was presented by Kansal and Tripathi [25], which works by measuring the PDF of the image followed by calculation of the adaptive parameter based on the average and highest amounts of the same PDF. Then, a thresholding limit is applied to the parameter modifying both the PDF and CDF. Next, calculating an adaptive parameter from the modified CDF to create a new CDF. Then, the new CDF is employed with the standard HE method to get the resulting image.

Besides, a sigmoid approach that depends on a sensitivity model was presented by Park et al. [26], in which it depends on contrast perception of the illumination sensitivity of the human eye. In this approach, the log-intensity level has an exponential function that determines contrast sensitivity. Using this notion, the sigmoid-based approach is developed by altering the Steven law exponent. In addition to this model, another method is presented that maintains the mean brightness and extends the histogram to reduce the loss of information, which they have called a parameter optimization method. Singh and Bhandar [27] proposed an algorithm that provides a balanced enhancement while preserving brightness and local details, in which different transformation functions are used to reach expected results. This method comprises primarily of four procedures: process the input's histogram and transform its gamma, perform a logarithmic process on the histogram, split the obtained histogram into smaller ones, and finally filter every small histogram by the standard histogram equalization.

In a later work, Veluchamy and Subramani [28] develop their previous model in [24] by including the fuzzy concept in their algorithm. In this method, the FDH is computed from the neighboring pixels. Next, a mapping strategy that depends on the intensity is made from the FDH and is employed for contrast amendment. In the end, a gamma adjustment approach is used to lighten dimmed areas of the image. Lastly, a new adaptive technique was presented by Srinivas et al. [29] through which they generate a novel numerical relative resemblance histogram depending on the concept of neighboring pixels' likeness while taking into consideration the image's standard deviation. Besides an adaptive color recovery method is created depending on the reworked luminosity rate of the HE processes and chromatic information that originally exists.

From the reviewed algorithms, different realizations are attained. First, improving the contrast can be achieved with different concepts. Second, some algorithms utilize sophisticated calculations to produce the outcome. Third, although some algorithms provide an adequate improvement for contrast, they also introduce processing errors and artifacts to the enhanced images. Forth, some methods tend to increase the brightness and degrade the colors when improving the contrast. Fifth, some algorithms require numerous inputs. Therefore, the opportunities still stand for developing an algorithm that utilizes a simple concept, few computations, improves the contrast while preserving brightness and adequate color representation, and does not introduce any unwanted processing errors or artifacts.

Hence, the HLIPSCS algorithm is proposed to achieve the aforesaid goals, in that its name came from the use of hyperbolic functions (H), logarithmic image processing (LIP), statistical methods (S), and contrast stretching (CS). The HLIPSCS algorithm can be used to ameliorate the contrast of both grayscale and color images supposed to be naturally distorted. The main contribution of this study is combining different low-complexity methods to produce a worthy algorithm. Evaluating the algorithm is done by comparing it against eight different algorithms and the quality of the comparison outcomes is measured using three dedicated image evaluation metrics with the consideration of run-times as well. Based on the outcomes, a deep analysis is made, and judgments are established. The remaining parts of this study are structured in the following way: In Section 2, the HLIPSCS algorithm is described extensively. In Section 3, everything related to the experiments, results, comparisons, discussions, and analysis is given, while in Section 4, laconic conclusions are provided.

2. Proposed HLIPSCS Algorithm

The main aims behind creating this method are as follows: Firstly, provide efficient processing for various grayscale and color images with deficient contrast representations. Secondly, generate the results rapidly without introducing any processing flaws, and thirdly, provide one parameter that controls the enhancement amount so that it becomes easier for the operator to produce the desired results. To reach the aforesaid aims, several processing notions have been utilized.

The novelty of this algorithm compared to the existing ones is in fact the use of the least number of pre-existing processing models and adapt some of them to create a new framework that can improve the contrast expeditiously. The working mechanism of this algorithm can be simply explained as follows: at first, the input image is processed by two different hyperbolic functions. Next, the outputs of these functions are combined using an adapted LIP model. After that, further processing is made by two modified statistical-based methods. Finally, a contrast stretching method is applied to produce the algorithm's output.

Going into specific details, the input is a contrast-distorted image and the numerical value of δ, which is responsible for controlling the amount of enhancement. After the input is made, the inputted image is sent to be processed by two different hyperbolic functions which are hyperbolic tangent [30] and hyperbolic sine [31]. These two functions perform an S-curve transformation on the image and have been proven to alter the tonality [32]. These two functions can be accurately written as:

$$HT = \frac{exp(I) - exp(-I)}{exp(I) + exp(-I)} \tag{1}$$

$$HS = \frac{exp(I) - exp(-I)}{2} \tag{2}$$

where I represents the input contrast-distorted image; HT is an image that results from processing image I by the hyperbolic tangent; HS is an image that results from processing image I by the hyperbolic sine. The next step signifies combining the features of HT and HS images using an adequate LIP model to create a different unique image with the features of both images, in that no transformation can create such an outcome. In [33], the authors have studied different LIP models and then proposed a new model that is better than the studied ones. The newly proposed model in [33] can be written as:

$$L = \sqrt[m]{1 - \frac{(1-u^m)\cdot(1-v^m)}{1-u^m\cdot v^m}} \tag{3}$$

where, L is the result of the LIP model; u is the first image; v is the second image; $(\cdot)$ is a multiplication operator; to get a logarithmic-like model, m=1. To adapt this model, a heuristic approach was followed, in that it ended by obtaining this equation which can adequately combine the results of the hyperbolic functions:

$$L = \left[1 - \frac{(1-HT^2)\cdot(1-HS^2)}{1-HT^2\cdot HS^2}\right]^{\delta} \tag{4}$$

where, δ is a parameter that holds the enhancement value, where $\delta > 0$, in that a greater value yields better enhancement in terms of contrast. δ should be manually determined by the operator to get the desired enhancement. Next, the contrast of the pristine image is further improved via the use of another altered method. As known, the sigmoid function (SF) is another S-curve transformation function that has been used to improve the image contrast in many research papers affiliated with contrast amendment [34], [35], [36]. The SF is expressed as follows [37]:

$$F = \frac{1}{1+exp(-I)} \tag{5}$$

This function will be used as a transformation function so that each pixel in the pristine image is raised to the power of an altered counterpart of the sigmoid function which can provide a non-linear contrast enhancement for the input image depending on the S-curve and LIP methods that have been previously used. Therefore, the input image is enhanced using the following equation:

$$S = (I)^{\left(\frac{\delta-1}{1+exp(-L)}\right)} \tag{6}$$

where S represents a contrast-enhanced version of the input image. Next, the brightness of S should be improved as well as in the contrast enhancement process, the brightness was reduced. Therefore, an improved version of the cumulative distribution function of Gompertz distribution (CDFGD) is used to achieve the aforesaid purpose. This distribution has been used previously in image enhancement research to improve brightness. In [38], the CDFGD is computed as:

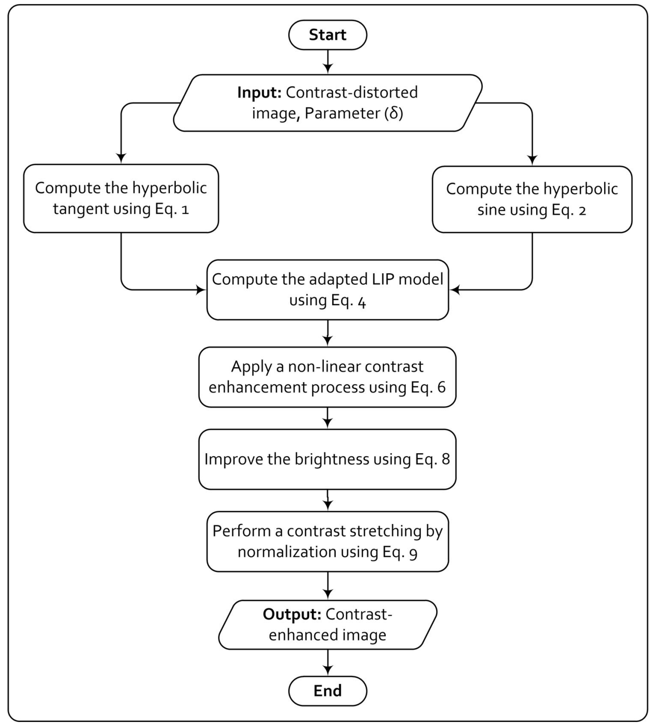

Figure 1. The HLIPSCS workflow illustration diagram.

$$w = 1 - exp\left(-\frac{\eta}{\gamma}\cdot(exp(\gamma\cdot I)-1)\right) \tag{7}$$

where, $(\eta > 0)$ and $(\gamma = 1)$, and η is a scalar that is liable for improving the brightness, wherein a greater value produces more brightness. In this study, the CDFGD is utilized in this form for brightness adjustment:

$$G = 1 - exp\left(-(0.4\cdot\delta)\cdot(exp(S)-1)\right) \tag{8}$$

Currently, the brightness and contrast are altered in image G. Still, the distribution of its intensities is limited in a certain dynamic range. Therefore, a contrast stretching method such as normalization is employed to reallocate the values of G to the natural interval. The used normalization method is written as [39]:

$$N = \frac{G - min(G)}{max(G) - min(G)} \tag{9}$$

where N represents the ultimate output of the algorithm; *max* and *min* signify the greatest and least amounts. To truly understand how the proposed algorithm works, the workflow diagram in Figure 1 is given.

3. Results and Discussion

The required details related to the dataset, image evaluation methods, comparison methods, machine specs, results, and analysis are made available in this section. As for the dataset, more than one hundred color and grayscale images were collected from different internet websites, in that all these images are real contrast distorted. These images were used for experimental tests and some color images were used for the comparison trials. As for the image evaluation methods, three of such are utilized to determine the perceived quality of the results attained from the proposed and the comparison methods. These methods are namely spatial frequency (SF) [40], natural image quality evaluator (NIQE) [41], and reduced-reference image quality metric for contrast change (RIQMC) [42].

The SF is a no-reference approach of measurement that assesses the total activity level in each image by detecting its vertical and horizontal frequencies This can help in identifying the visibility of spatial image information, in that images with better visible features usually have higher perceived spatial information. The NIQE is a metric with the type of no-reference that determines the image's naturalness depending on natural scene statistics and statistical features analysis, in that its scores can be affected by brightness and contrast distortions. This means that it can detect the contrast and brightness changes in the evaluated images as a part of the naturalness feature. The RIQMC is a reduced-reference metric that assesses the amount of brightness and contrast change by utilizing certain statistical information taken from the image histogram with the aid of the phase congruency concept.

This metric is specialized in detecting the amount of brightness and contrast change between a filtered image and its associated degraded observation. The production of these three evaluation approaches is a number, in that a higher value indicates better information visibility for SF, better naturalness for NIQE, and worsened contrast quality for RIQMC, as for this metric, lower results indicate better quality results. As for the full-reference image evaluation methods such as the peak signal to noise ratio (PSNR) and mean square error (MSE), such methods cannot be used in this study because the utilized images are real contrast distorted, and the ideal (reference) version of these images is not available. Regarding the comparison methods, eight algorithms that utilize different processing concepts were used to be compared against the proposed HLIPSCS algorithm. Their working mechanisms are briefly explained in Section 1 of this article, in that the comparison algorithms are AIVHE, AGCWD, MMSICHE, DS, RESIHE, OGCWS, HEOPC, and FC.

The computer device that is used to perform the experiments and comparisons has a 2.8 GHz Core i7-7700 CPU, Nvidia GeForce GTX 1050 GPU, and 16 GB of memory. The environment used to run all the codes is MATLAB 2018a. Figure 2 to Figure 4 demonstrate the experimental results with different grayscale images. Figure 5 to Figure 7 exhibit the experimental outcomes with different color images. Figure 8 to Figure 11 display the results of comparisons. Table I provides the readings of the used image evaluation methods and implementation times. Figure 12 to Figure 14 depict the average performances of Table I. From the outcomes of experiments on different grayscale and color images in Figure 2 to Figure 7, it can be observed that adequate performances have been obtained by the proposed algorithm. Regarding the grayscale images, the contrast has been significantly improved, the brightness has been suppressed from being amplified, and the overall appearance of the results appears way better than their pristine observations. As for the color images, the original brightness has been preserved, the contrast has been

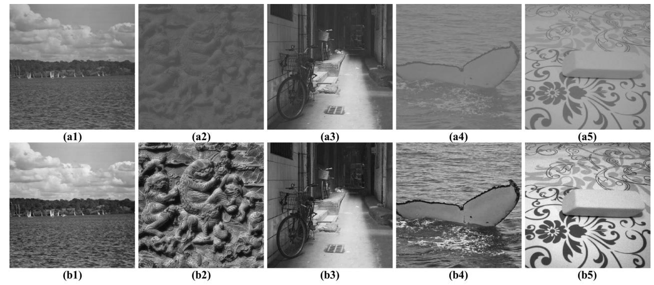

Figure 2. Processing different grayscale images (Set 1). (a1-a5) real contrast-distorted images. (b1-b5) filtered by HLIPSCS with δ = (3.5, 5, 2, 4, 6).

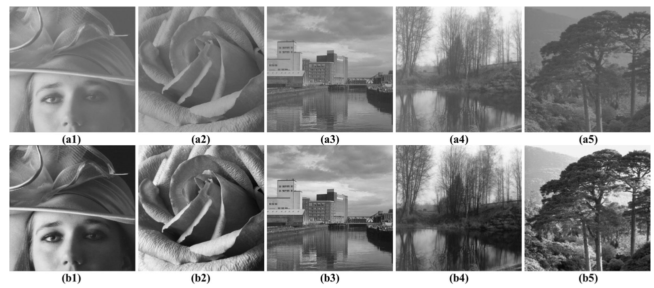

Figure 3. Processing different grayscale images (Set 2). (a1-a5) real contrast-distorted images. (b1-b5) filtered by HLIPSCS with δ = (4, 5, 3.5, 2, 3).

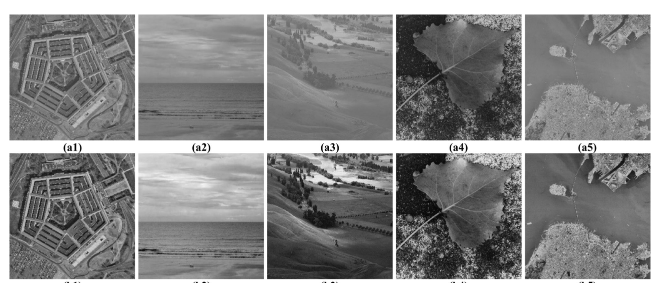

Figure 4. Processing different grayscale images (Set 3). (a1-a5) real contrast-distorted images. (b1-b5) filtered by HLIPSCS with δ = (5, 2.8, 3, 3.5, 5.5).

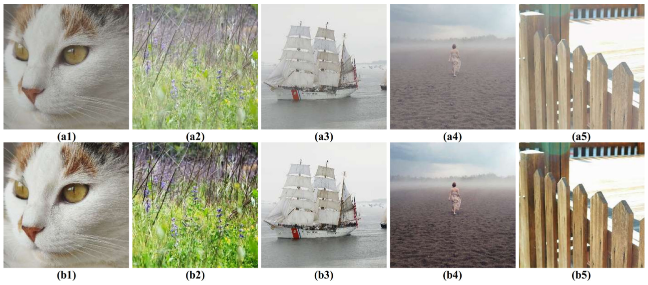

Figure 5. Processing different color images (Set 1). (a1-a5) real contrast-distorted images. (b1-b5) filtered by HLIPSCS with δ = (4.5, 7.5, 5, 6.5, 7).

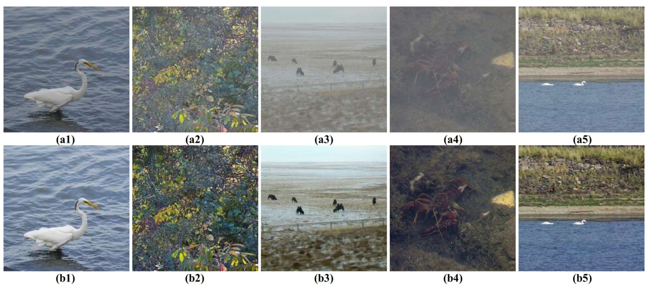

Figure 6. Processing different color images (Set 2). (a1-a5) real contrast-distorted images. (b1-b5) filtered by HLIPSCS with δ = (3.8, 5.5, 4, 3, 5).

noticeably ameliorated and the colors appear more vivid when compared to the unprocessed counterparts.

The outcomes of the proposed algorithm own a natural appearance as well as, no visible processing flaws have been seen in the results. The results appear as if a coat of mist has been pulled out from the images while preserving important details and revealing the key image traits properly. This is important because a low-complexity structure has been used to achieve such results, in which it does not require many calculations. From the comparison results that are demonstrated in Figure 8 to Figure 14 and Table I, it can be observed that different performances are obtained. The performance of each metric has been labeled from worst to best as worst, 2nd worst, low, below moderate,

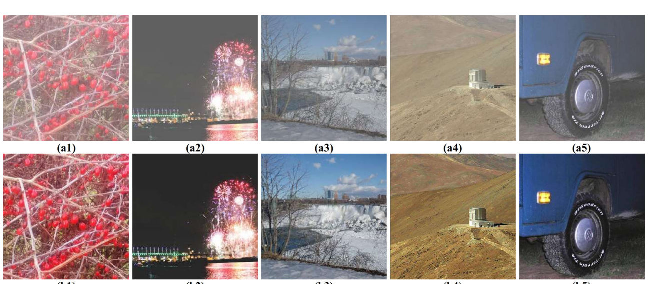

Figure 7. Processing different color images (Set 3). (a1-a5) real contrast-distorted images. (b1-b5) filtered by HLIPSCS with δ = (7, 6.5, 4, 7.5, 5.5).

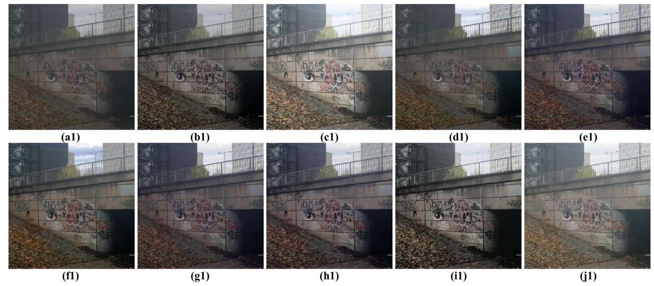

Figure 8. The outcomes of the accomplished comparisons. (a1) real-contrast degraded color image. Other images are filtered with: (b1) AIVHE; (c1) AGCWD; (d1) MMSICHE; (e1) DS; (f1) RESIHE; (g1) OGCWS; (h1) HEOPC; (i1) FC; (j1) Proposed HLIPSCS.

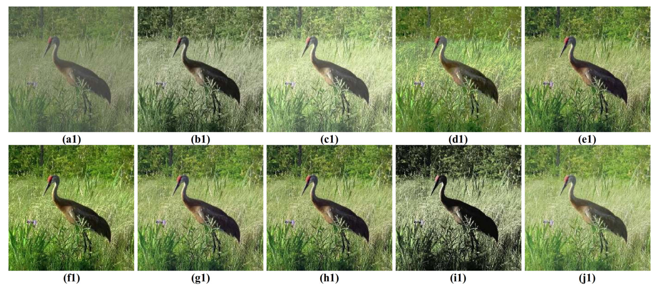

Figure 9. The outcomes of the accomplished comparisons. (a1) real-contrast degraded color image. Other images are filtered with: (b1) AIVHE; (c1) AGCWD; (d1) MMSICHE; (e1) DS; (f1) RESIHE; (g1) OGCWS; (h1) HEOPC; (i1) FC; (j1) Proposed HLIPSCS.

moderate, above moderate, well, 2nd best, best. Regarding the implementation times, they will be analyzed depending on the scored rank.

The AIVHE algorithm produced results with slightly pale colors, blackened some areas with peculiar brightness. That is why it scored the worst in SF, 2nd worst in NIQE, and below moderate in RIQMC. This means that although it produced somewhat sufficient contrast, the other mentioned undesirable observations have affected the overall visibility. As for the processing time, this algorithm was ranked the fastest in the comparison. The AGCWD algorithm produced results with light colors and increased brightness. That is why it scored low in SF, 2nd best in NIQE while scoring low in RIQMC. This means that although it produced an image with high visibility, the contrast is not stretch to all the natural range. As for the processing time, this algorithm was ranked the 2nd fastest in the comparison.

The MMSICHE algorithm introduced some processing errors to the results. That is why it scored 2nd best in SF, moderate in NIQE, and above moderate in RIQMC. This means if the processing errors can be avoided, this method world provide better image evaluation scores. As for the processing time, this algorithm was ranked 7 out of 9 in the comparison. The DS algorithm produced results with slightly dark colors and blackened few areas. That is why it scored moderately in SF, below moderate in NIQE, and

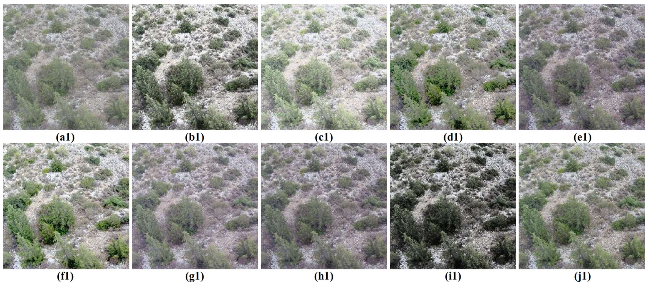

Figure 10. The outcomes of the accomplished comparisons. (a1) real-contrast degraded color image. Other images are filtered with: (b1) AIVHE; (c1) AGCWD; (d1) MMSICHE; (e1) DS; (f1) RESIHE; (g1) OGCWS; (h1) HEOPC; (i1) FC; (j1) Proposed HLIPSCS.

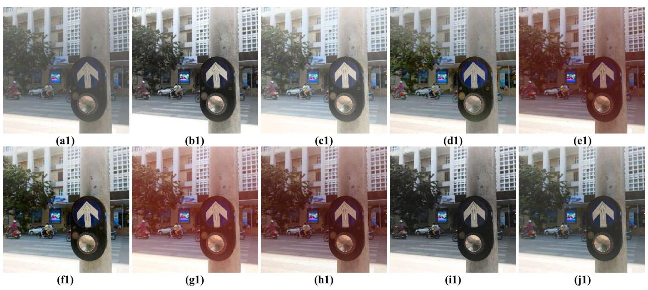

Figure 11. The outcomes of the accomplished comparisons. (a1) real-contrast degraded color image. Other images are filtered with: (b1) AIVHE; (c1) AGCWD; (d1) MMSICHE; (e1) DS; (f1) RESIHE; (g1) OGCWS; (h1) HEOPC; (i1) FC; (j1) Proposed HLIPSCS.

2nd best in RIQMC. This means that further improvements must be applied to this algorithm to deal with the aforesaid drawbacks to produce better quality results. As for the processing time, this algorithm was ranked 5 out of 9 in the comparison.

The RESIHE algorithm produced results with dark colors and blackened many areas. That is why it scored below moderate in SF, well in NIQE, and 2nd worst in RIQMC. This means that even though the resulting images perceived better than the originals, producing unnatural contrast, brightness, and colors with many blackened image areas led to the loss of important information. As for the processing time, this algorithm was ranked the 2nd slowest in the comparison. The results of the OGCWS and HEOPC algorithms may seem very much similar, but when viewing the results with full-size, differences can be noticed. The HEOPC algorithm scored well in SF, worst in NIQE, and moderate in RIQMC due to the presentation of minor processing flaws. As for the implementation time, it was ranked 6 out of 9. The OGCWS algorithm scored above moderate in SF, low in NIQE, and well in RIQMC. Still, the OGCWS was the slowest algorithm in the comparison.

The FC algorithm produced results with unfamiliar colors and blackened huge areas. That is why it scored 2nd worst in SF, above moderate in NIQE, and the worst in RIQMC. This means that a huge amount of important

TABLE I. The scored image evaluation readings and the execution times of the compared algorithms.

Methods	Figure	SF	NIQE	RIQMC	Time
	Fig.8	0.346	3.458	10.546	0.181
	Fig. 9	0.687	4.766	20.617	0.172
AIVHE [15]	Fig. 10	0.375	3.173	14.425	0.087
	Fig. 11	0.164	3.423	11.819	0.102
	Avg	0.393	3.705	14.352	0.1355
	Fig.8	0.537	3.548	15.829	0.220
	Fig. 9	0.695	4.809	18.032	0.178
AGCWD [16]	Fig. 10	0.368	3.702	13.034	0.114
	Fig. 11	0.127	3.862	10.748	0.156
	Avg	0.431	3.980	14.410	0.167
	Fig.8	0.400	3.355	11.142	16.011
	Fig. 9	0.691	4.741	21.409	13.629
MMSICHE [17]	Fig. 10	0.530	3.846	13.731	5.630
	Fig. 11	0.169	3.546	9.984	12.111
	Avg	0.447	3.872	14.066	11.845
	Fig.8	0.416	3.229	10.705	0.977
	Fig. 9	0.691	5.021	20.645	0.808
DS [18]	Fig. 10	0.513	3.720	8.094	0.413
	Fig. 11	0.111	3.201	9.395	0.708
	Avg	0.432	3.792	12.209	0.726
	Fig.8	0.334	3.427	12.221	19.404
	Fig. 9	0.677	4.787	23.860	17.767
RESIHE [19]	Fig. 10	0.539	3.955	14.431	6.112
	Fig. 11	0.174	3.602	11.771	14.275
	Avg	0.431	3.942	15.570	14.389
	Fig.8	0.390	3.289	11.323	28.663
	Fig. 9	0.701	4.980	21.053	31.454
OGCWS [20]	Fig. 10	0.514	3.804	8.730	11.648
	Fig. 11	0.125	3.038	10.177	21.583
	Avg	0.432	3.777	12.820	23.337
	Fig.8	0.365	3.344	13.049	1.004
	Fig. 9	0.682	4.859	21.622	0.826
HEOPC [21]	Fig. 10	0.500	3.655	9.776	0.499
	Fig. 11	0.195	2.923	12.205	0.837
	Avg	0.435	3.695	14.163	0.791
	Fig.8	0.310	3.469	15.876	0.459
	Fig. 9	0.664	4.575	26.651	0.538
FC [22]	Fig. 10	0.477	3.731	15.110	0.240
	Fig. 11	0.175	3.837	10.091	0.408
	Avg	0.406	3.903	16.932	0.411
	Fig.8	0.575	3.358	10.538	0.344
	Fig. 9	0.708	5.044	16.716	0.322
Proposed HLIPSCS	Fig. 10	0.551	3.819	7.283	0.126
	Fig. 11	0.193	3.919	6.407	0.283
	Avg	0.506	4.035	10.236	0.268

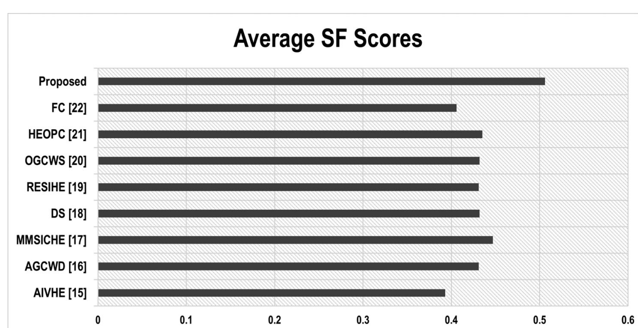

Figure 12. A pictorial illustration of the average SF measures in Table I.

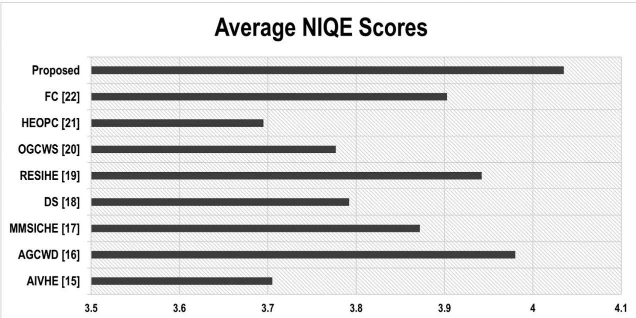

Figure 13. A pictorial illustration of the average NIQE measures in Table I.

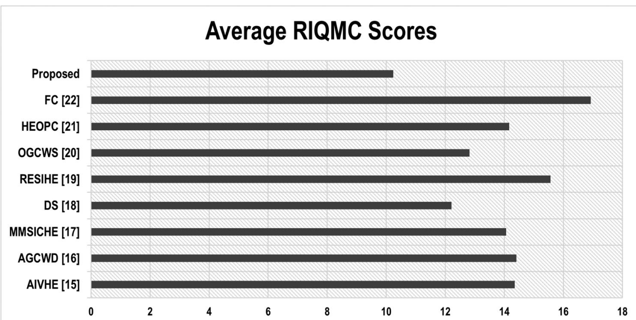

Figure 14. A pictorial illustration of the average RIQMC measures in Table I.

information and details were lost in the recovered images. As for the processing time, this algorithm was ranked 4 out of 9 in the comparison. The proposed HLIPSCS algorithm scored the best in all the used metrics since its results own suitable contrast, well-preserved illumination, and vivid color depictions. Besides, no processing errors were seen in the results, and it was ranked the 3rd fastest algorithm in the comparison. This can be described as a fruitful accomplishment as visually pleasing results were obtained by utilizing low calculations, which makes this algorithm desirable to be used with imaging modalities that have low-hardware qualifications.

4. Conclusion

An algorithm named HLIPSCS is introduced in this study for contrast adjustment of color and grayscale images. This algorithm utilizes different concepts such as statistics, hyperbolic functions, contrast stretching, and logarithmic image processing. The algorithm is tested with images that have natural-contrast diminution, as well as comparisons and results evaluations were conducted. Using the obtained outcomes, it can be understood that not all algorithms in this field can produce satisfactory results, some existing algorithms have high computations, and some other algorithms require numerous inputs. These issues were considered when the HLIPSCS was developed, in that it provided satisfactory performances as it was able to recover different color and grayscale images efficiently and rapidly. Accordingly, the results have way better visual quality when compared to the original counterparts. As for the important image traits, the brightness is preserved, the contrast is improved, and the colors appeared more vivid. Besides, it outperformed the comparison algorithms as indicated by the employed image evaluation metrics. This is an important issue because a simple structure and low calculations were employed by the HLIPSCS. As future works, the HLIPSCS can be made utterly automatic or can be amended to work with systems that have low specs.

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