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Original Article

A Novel Approach for Enhancing Contrast for Digital Images

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Abstract - Improving contrast is crucial for increasing autonomous decision-making and visual appeal in a range of industrial applications. This study offers a unique technique for altering the tonality of a variety of photographs, including gray scale or colour contrast-distorted photos and medical images. It is based on Stevens' Power Law (SPL), which is derived from human brightness perception. The proposed method improves the overall tonal look of the image by accounting for the non-linear relationship between intensity and perception. The first stage involves tonal correction using SPL, which allows precise fine-tuning of brightness levels dependent on intensity values in order to get the optimum tone and enhance visual enticement. The sigmoid function is employed to enhance contrast by amplifying pixel brightness variations between adjacent pixels in a targeted manner. This preserves crucial details and refrains from over-amplification, all while enhancing contrasts overall. Two primary benefits of the proposed method are its reduced computational complexity and its ability to offer excellent visibility. By employing SPL and the sigmoid function, the processing needs are decreased without compromising the quality of the output. This renders the proposed method both efficient and appropriate for real-time image processing applications. Experiments' results demonstrate how the proposed method may be applied to tone adjustments, contrast enhancements, processing artifact removal, and other visual quality enhancements for a wide range of photo types. Performance comparisons with other algorithms demonstrate the method's significant improvement in effectiveness and efficiency.

Keywords - Steven's power law, Contrast enhancement, Contrasts stretching, Histogram equalization, Human visual perception.

1. Introduction

Contrast is a crucial visual element that is vital to our perception and understanding of images. It explains how the various elements of a picture differ in terms of brightness, colour, or intensity. A picture's ability to convey visual information and enhance its visual quality depends on the amount of contrast. Researchers have offered various enhancing procedures to improve the photographs' visual quality. A technique called Contrast Enhancement (CE) is used to improve an image's appearance so that it is more suited for human vision. CE typically consists of a number of actions, like enhancing the differences in size between items in the foreground and background.

The field of image enhancement is important for computer vision and human perception since CE approaches can increase an image's brightness and/or contrast to magnify features and make them easier to see. Applications and industries where CE is frequently utilized include medical imaging, remote sensing, biology, video surveillance, satellite image processing, and geographic research. Numerous CE algorithms aim to enhance features of image quality, such as colour representation, noise tolerance, brightness preservation, and consistent contrast. Direct and indirect procedures are the two categories of CE methods [1]. The evaluation of image contrast is achieved through the application of various nonlinear functions [3] or by solving optimization issues [4]. Direct approaches based on the Human Visual System (HVS), such as the Weber-Fechner law or Retinex theory [2], are also used to assess image contrast.

While direct approaches yield 'halo' aberrations, especially around sharp edges, and have significant processing complexity, they offer certain advantages in terms of image detail augmentation and dynamic range reduction [5]. High picture contrast and real-time processing without appreciable distortion are still difficult to achieve, even with the development of novel direct techniques to address these issues. In practice, indirect procedures based on a global transformation function are more often used than direct methods for the following reasons: one of the most widely used indirect procedures, Histogram Equalization (HE), produces visual distortions such as noise amplification, contouring, or significant brightness change when the image histogram contains high peak values [6].

By adjusting the image histogram to reduce high peak values before obtaining the transformation function from the modified histogram, a number of HE-based methods overcome these challenges. The construction of the image histogram using a Two-Dimensional (2D) histogram [7] or fuzzy contextual information [8], which gives pixels in texture regions more weight, are two recent indirect methods for maintaining detail. These methods reduce information loss and increase performance over previous indirect methods.

A multitude of algorithms have been introduced on CE over the years, varying in complexity and calculational ease of use. A technique known as Recursively Separated Exposure-Based Sub-Image Histogram Equalization (RS-ESIHE) was presented by Singh et al. [9] in their study. It separates the image histogram in a recursive manner, further separates each new histogram according to its own exposure threshold, and equalizes each sub-histogram separately. An Optimal Gamma Correction and Weighted Sum (OG-CWS) technique was developed by Jiang et al. [10] with the goal of enhancing contrast without sacrificing average. Wong et al. [11] created the Histogram Equalization and Optimal Profile Compression (HE-OPC) technique to improve an image's colour vibrancy.

It then uses a more recent HE technique that compresses undesired artifacts to adjust the image's intensity after translating the primary colours into linked human perceptual zones. Parihar et al. [12] presented a Fuzzy Contextual (FC) approach for colour and grayscale photos. The selected algorithm amplifies intensity changes according to the local relative information of the exact image. Contextual data can be included by using a Fuzzy Dissimilarity Histogram (FDH). In recent years, a lot of research has focused on Convolutional Neural Networks (CNNs) in particular to improve pictures. To the best of our knowledge, however, most deep learning-based methods have not been developed for natural picture augmentation but rather for medical shots [9], low-light images [13], or fuzzy images [14].

Zohair et al. [15] proposed a fast and efficient image contrast enhancement algorithm (HLIPSCS). This technique, which made use of numerous ideas, including statistics, hyperbolic functions, contrast stretching, and logarithmic image processing, produced better brightness preservation, improved contrast, and more vivid colours.

2. Related Literature

In comparison to other contrast enhancement techniques, such as [9-12], Zohair et al.'s method [15] offers: (a) efficient processing for a variety of grayscale and color pictures with poor contrast representations, (b) produce the output quickly while avoiding processing errors, and (c) provide an enhancement amount control parameter in order to make it simpler for the operator to get the desired outcomes.

The following straightforward explanation will show how their approach functions: firstly, two separate hyperbolic functions process the input picture. Next, a LIP model is used to integrate the output of these functions. The contrast of the picture is then improved by using a nonlinear transformation function in the form of a sigmoid function. After that, a statistical processing technique is used to enhance the image's brightness. And last, normalization, which is the final algorithm output, does contrast stretching. Better brightness preservation, enhanced contrast, and more vibrant colours are the results of this algorithm, using many concepts like statistics, hyperbolic functions, contrast stretching, and logarithmic image processing.

In their method, hyperbolic functions were added to enhance an image's tonality. However, these functions induce a fast rise in pixel value, which in turn leads to a compression of the tonal range overall and a loss of details. Additionally, hyperbolic functions do not offer precise control over the tone-mapping procedure. Due to the mathematical definition of these functions, they do not provide modifiable parameters that can be easily modified to achieve the desired tonal alteration. Additionally, it can be computationally expensive to calculate hyperbolic functions for larger photos. In time-sensitive applications or real-time scenarios, this complexity may result in an increase in the processing time needed for tone augmentation. In addition to hyperbolic functions, their method combines hyperbolic tangent and sine characteristics with LIP models to produce distinctive images. LIP model performance significantly depends on the caliber, variety, and representation of training data. LIP models are used to combine hyperbolic sine and tangent features, which involves complex calculations needing a lot of computational power and processing time.

Nevertheless, despite improvements in CE methods, there is still room for an algorithm to be developed that performs better in terms of simplicity, effectiveness, and maintaining both brightness and colour representation. Such an algorithm should make an effort to reduce processing mistakes and prevent the introduction of undesirable artifacts. A unique technique can significantly increase CE by resolving these issues, resulting in improved visual quality and correct perception of picture details.

3. Background

3.1. Human Brightness Perception

The brain's interpretation of the various light wavelengths picked up by the cone cells in the retina is what allows humans to see colour. Cone cells, which are sensitive to the three fundamental colours red, green, and blue, are in charge of color vision. To perceive a variety of colors, the brain analyses the data from these cones. Color spaces, like the Red-Green-Blue (RGB) color space, can be used to explain how colors are perceived. A combination of red, green, and blue intensities in the RGB color model represents each color. In an 8-bit color depth system, intensities vary from 0 to 255, with higher numbers signifying higher intensities.

The brain uses the variations in pixel intensities to detect changes in intensity in an image. Mathematical formulas and models can be used to explain how the brain reacts to variations in intensity. Weber's law [16], which asserts that the perceived change in intensity is proportionate to the starting intensity, is one widely used model. It can be written mathematically as:

$$dI/I=k \tag{1}$$

Where ‘k’ is a constant known as Weber's fraction, I stands for the original intensity, dI stands for the intensity change. The sensitivity of the human brain to intensity fluctuations is determined by Weber's fraction. A lower value of ‘k’ denotes increased sensitivity to intensity variations.

The idea of brightness is a key one in the perception of color. Luminance, which is obtained from the RGB color values, stands for the brightness or intensity of a picture.

3.1.1. Human Perception Based Steven's Power Law

Based on SPL [17], it is hypothesized that human perception has a non-linear connection with physical stimulus intensity for a variety of sensory inputs, such as brightness, loudness, and perceived magnitude. This connection is described mathematically by SPL.

The physical intensity (I) increased to a power (n) determines the perceived magnitude (P) of a stimulus in accordance with SPL. It has the following mathematical expression:

P=K*I^n (2)

In this equation, 'n' is a parameter that controls how steep the connection is, and 'K' is a constant. The sensitivity of perception to variations in physical intensity is indicated by the value of 'n'. Small increases in intensity translate into bigger apparent changes in magnitude when 'n' is larger, indicating a steeper connection. A lower number of 'n', on the other hand, denotes a shallower connection, with smaller perceived changes in magnitude for a given change in intensity.

According to SPL, the physical strength of a stimulus does not necessarily rise linearly with our perception of it. Instead, depending on the magnitude of n, it has a compressive or expanding impact. These properties of our sensory systems, which adapt and react differently to varied intensities, are reflected in this nonlinear connection.

For instance, SPL suggests that our perception of brightness does not rise in direct proportion to the physical luminance in the context of brightness perception. The perception of modest increases in brightness at lower intensities is stronger than that of small increases at higher intensities. Our visual system can successfully adjust to a broad variety of brightness levels thanks to this non-linear connection, emphasizing features in darker areas while retaining and discriminating in brighter areas.

Understanding human perception in terms of SPL can help us better understand how our sensory systems react to stimuli and can also help us create perceptually correct methods for processing images and sounds. We may create algorithms and models that take into account these perceptual qualities by taking into account the non-linear structure of perception, which will eventually result in more accurate and useful sensory experiences to achieve the aforementioned goals, "Dynamic Contrast Enhancement using Power Sigmoid" is proposed.

4. Proposed Work

The main reasons behind introducing SPL in the proposed method are: (a) SPL seeks to preserve the image's perceptual linearity, which means that variations in pixel values more closely match how people perceive things. This provides a more attractive and realistic-looking image, and (b) the exponent parameter of SPL enables precise control of the tone mapping procedure.

This parameter allows for more freedom in tone modifications by allowing the transformation to be tailored to certain image attributes or artistic preferences, and (c) compared to the hyperbolic functions, the power law transformation maintains more picture details. This implies that significant details and minute differences in the picture may be more effectively preserved, leading to a more accurate depiction of the original image.

Going into specific details, consider an input image, which may be medical photos, satellite images, underwater images, or images with altered contrast. To begin, apply SPL transformation to the supplied image. Each pixel value in the image is increased to the power of 'k', resulting in a transformed image given by:

$$\boldsymbol{P} = \boldsymbol{I}^{\boldsymbol{k}} \tag{3}$$

This non-linear adjustment modifies the image's intensities, emphasizing higher values and potentially increasing contrast. The contrast of the idealized image is enhanced even further. The converted picture P is then put through a Sigmoid Function (SF) [18], which is the S-curve transformation function utilized to enhance contrast in several research articles [19]. The SF is defined as:

$$\boldsymbol{SF} = \frac{\mathbf{1}}{\mathbf{1}+\boldsymbol{e}^{-\boldsymbol{P}}} \quad (4)$$

The sigmoid function maps the pixel values using a non-linear mapping, compressing the intensity range and extending the values towards the extremes.

In the CE process, the brightness of the image should be improved. Here, an improved version of CDF of Gompertz distribution [20] is used in order to increase the brightness, which is utilized as:

$$\boldsymbol{G} = \mathbf{1} - \boldsymbol{e}^{\{-(\mathbf{0.4}*\boldsymbol{d})*(\boldsymbol{e}^{\boldsymbol{SF}}-\mathbf{1})\}} \quad (5)$$

The 'd' parameter controls the enhancement effect, with larger values resulting in more pronounced enhancement. Finally, the generated image G is adjusted for intensity by using a method called normalization, which scales the intensity values to the full dynamic range. The normalization function is given as [21]:

$$\boldsymbol{CE} = \frac{[\boldsymbol{G}-\mathbf{min}(\boldsymbol{G})]}{[\mathbf{max}(\boldsymbol{G})-\boldsymbol{min}(\boldsymbol{G})]} \quad (6)$$

This adjustment guarantees that the improved image, denoted by CE, makes full use of the available pixel value range, maximizing the CE impact and delivering a visually appealing outcome. Figure 1 shows the workflow diagram of the proposed method.

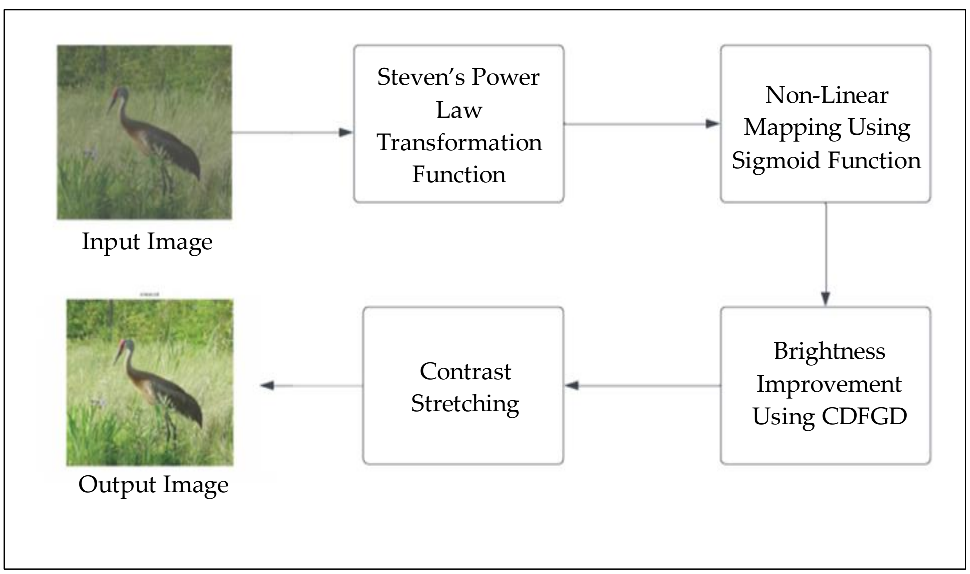


Fig. 1 Workflow diagram

5. Experimental Results

A number of tests are conducted to show how well the suggested algorithm works. Thousands of pictures were downloaded from the internet, and hundreds from the Berkley image data set [23], some of which were natural and others of which had true contrast distortion. Some of these photographs were utilized for comparison with current techniques, while others were used for experimental reasons. To compare the perceived quality of the outcomes obtained from the suggested and comparable approaches, two picture assessment methodologies are used. These techniques include Spatial Frequency (SF) [17] and the Natural Image Contrast Evaluator (NICE) [22]. More crucially, the suggested method's and the comparison method's execution times are compared. Assessing and quantifying the distribution of the numerous spatial frequencies seen in an image is the process of spatial frequency assessment in images. It involves looking at the patterns and variations in color or intensity at different scales or frequencies.

In order to capture several statistical aspects of the picture, such as gradients, local brightness statistics, and color attributes, the NICE method computes a collection of features. The quality score of the image is then estimated using these features. The perceived quality of the image decreases as the NICE score increases.

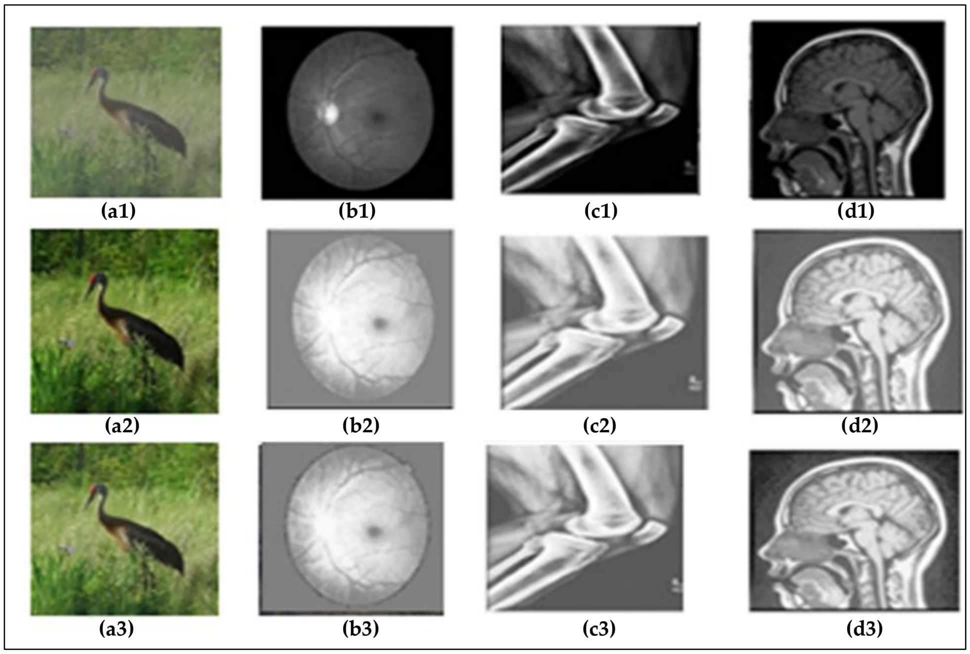


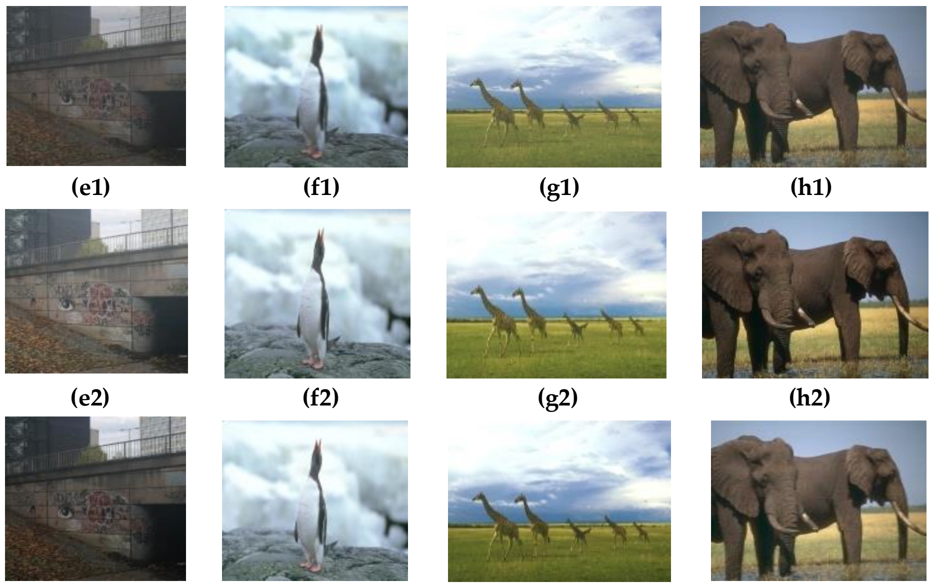
Fig. 2 Real contrast distorted images processed by [15] and the proposed method

NICE has the benefit of not requiring a reference picture, which makes it appropriate for assessing image quality when one is not readily available or practicable to produce. In real-time applications, including video processing, security systems, and medical imaging, CE techniques are frequently utilized. For the system to operate in real-time or to maintain a smooth user experience, these need rapid and responsive processing. Making ensuring the CE procedure can be completed within the appropriate time restrictions involves evaluating execution time. We used a computer system with a 2.8 GHz Intel Core i7 CPU and 16 GB of RAM to conduct the testing and comparisons. The environment used to execute all the programmes is MATLAB 2021a.

Figure 2 shows the experimental results of various real contrast distorted images and some medical images. Different images are processed separately to generate the perfect tone by altering the constant parameter "k" of SPL. This gives the hue mapping action fine-grained control and caters to the distinctive features and needs of each image. The hue may be successfully improved by choosing the right value of "k" for a given image, leading to aesthetically stunning effects that go beyond the capabilities of hyperbolic functions.

In comparison to the approach given in [15], the experimental results shown in Figure 2 and Figure 3 demonstrate how well our suggested method for CE performs. While ‘a2’ to ‘h2’ correspond to the contrast-enhanced versions of ‘a1’ to ‘h1’ using the approach in [15], ‘a1’ to ‘h1’ represent the input pictures. The contrast-enhanced pictures of 'a1' to 'h1' that were acquired using our suggested approach are represented similarly by 'a3' to 'h3'.

It is clear from the findings that our suggested strategy efficiently improves the tonality of the photos by adjusting the SPL's parameter "*k*". It is clear from comparing assessment metrics like NICE, SF, and processing time that our technique outperforms [15] in terms of visual quality and processing speed. Notably, the suggested technique delivers more vibrant colors while effectively maintaining the original brightness of color photographs, resulting in a natural look.



(e1) (f1) (g1) (h1)

(e2) (f2) (g2) (h2)

(e3) (f3) (g3) (h3)

Fig. 3 Real color images from the Berkley image data set [23] processed by [15] and proposed method

Table 1. The scored image evaluation readings and execution times of two compared algorithms

Image	Method [15]			Proposed Method		
	NICE	SF	Time	NICE	SF	Time
Fig. a1	5.825	0.76	0.186	5.274	0.67	0.154
Fig. b1	4.064	0.66	0.044	4.130	0.63	0.027
Fig. c1	3.124	0.68	0.027	2.767	0.62	0.008
Fig. d1	2.842	0.69	0.034	2.368	0.66	0.017
Fig. e1	3.559	0.61	0.197	3.409	0.58	0.138
Fig. f1	3.190	0.63	0.027	2.795	0.59	0.012
Fig. g1	2.928	0.60	0.038	2.589	0.58	0.024
Fig. h1	3.732	0.63	0.036	3.246	0.65	0.012
Average	3.658	0.657	0.065	3.322	0.622	0.049

The data from the two picture assessment approaches are shown in Table 1, which offers thorough insights into the effectiveness of several strategies, including our suggested method. Notably, our approach performs better than others in terms of effectiveness and processing speed. The suggested method's average NICE and SF values are greater than those of [15], demonstrating our method's superior performance in contrast augmentation. Our suggested solution also runs faster than [15], demonstrating its quickness and effectiveness among all.

Additionally, Table 2 compares the experimental outcomes for two authentically altered photos between our suggested approach and numerous previously described algorithms.

Table 2. Image evaluation readings of two measures, NICE and SF, for six methods

Method	Image	Parameters	
		NICE	SF
[09]	a1	4.787	0.677
	h1	3.427	0.344
[10]	a1	4.980	0.701
	h1	3.289	0.390
[11]	a1	4.859	0.682
	h1	3.344	0.365
[12]	a1	4.575	0.664
	h1	3.469	0.310
[15]	a1	5.025	0.661
	h1	3.359	0.575
Proposed	a1	5.374	0.689
	h1	3.509	0.598

The results shown in Table 2 shows that our approach has the best NICE and SF scores among all algorithms and the quickest execution time, further demonstrating its efficiency and effectiveness in comparison to other approaches.

6. Conclusion

An effective picture enhancement method for industrial use is proposed in this paper. The proposed method based on SPL outperforms the state of the art in terms of contrast, visual appeal, and processing time, and it allows for future tweaks to make the power law flexible. Furthermore, the method selectively enlarges changes in picture detail while maintaining crucial pixel brightness variations, improving overall contrast and tonal look. The experimental results demonstrate the enhanced efficacy and performance of the proposed approach, which holds potential for various image processing applications such as industry and healthcare 4.0.

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