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IMPROVING LOW ILLUMINATION IMAGE BASED ON MULTI-SCALE RETINEX VIA BILINEAR INTERPOLATION

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Abstract: Images taken at night in low-light situations are more likely to have poor visibility, which can affect future processing for outdoor computer vision applications. As a result, we recommend a retinex upgrade for nighttime image enhancement. Retinex is one of the most widely used techniques. It's used on photographs with non-uniform brightness in terms of colour or lightness, and it gets the job done in terms of colour consistency and dynamic range compression. Few studies have looked into retinex's performance on night-time photos, especially those taken in challenging conditions (i.e., images with over- or under-lit areas, or images with noisy speckles), where the technique can fall short. The original multi-scale retinex via Bilinear Interpolation (MSRBI) is particularly sensitive to camera noise speckles in low light, and it has a poor effect on areas with ordinary or irradiated light. In low-light circumstances, the original MSR is particularly sensitive to noise speckles produced by cameras, and it performs poorly in areas with normal or bright lighting. In addition, the original MSR used a gain-offset technique for pre-display processing, which could result in visible data loss on night-time images. This study replaces MSR's logarithm function with a customised sigmoid function to prevent data loss, and adapts MSRBI to night-time photography by combining sigmoid-MSR findings with original images.

***Index Terms* - Multi-scale retinex, Bilinear interpolation, sigmoid function, high-light preserving**

I. INTRODUCTION

When dealing with corrupted photos, there are a few techniques that can assist people improve the image quality; these systems are known as image improvement approaches. Image enhancement [1] [2] is a method for repairing and increasing the quality of defective images. The main motivation for image enhancement is to improve the qualities of a picture for human perception [3] [4]. That used as a model of human colour constancy in the late 1990s. In today's world, we have a wide range of possibilities for enhancing our image. Retinex is a very effective and efficient procedure that can be utilised to meet the demand for a feasible image improvement. The image of a location in the human visual framework is shaped in our brains with the help of the human eye (Retina) and brain processing when we gaze at it. The fundamentals of Retinex are founded on the entire situation of how a viewpoint is seen by the human visual framework. The term "Retinex" was coined from the combination of two words (retina" and "cortex"). Due to a variety of variables, it's possible that an image captured by a machine will have a poorer dynamic range or poor colour consistency. There has been a slew of problems with photographing in low-light circumstances. The nighttime environment was found to be more intricate than the daylight environment. In comparison to natural light during the day, the light at night is judged insufficient. As a result, the photos were dark, blurry, low-contrast, indistinct features, and had restricted dynamic range compression. Prior techniques, such as Histogram equalisation [6] [7], led in noise amplification when images had low intensity sections. When used directly on night-time photos, the original multi-scale retinex (MSR) [8] [9] may display the following flaws: (1) The clipping process utilised prior to display can cause data loss, especially in areas that are highlighted or unlit. This type of area is particularly common in nighttime shots, in contrast to photographs taken during the day. (2) The nature of Retinex tends to highlight the lightness difference between pixels in order to increase clarity, which can drastically exacerbate the noise impact in night-time images with a lot of noise [10]. To begin, we propose replacing the logarithm function with a tailored sigmoid function that functions similarly to the logarithm function but is cleanly limited and only compresses the lightness near its limits. As a result, there is no need for clipping and no data loss [11] [12]. It's a monotonically increasing function with easily adjustable upper and lower bounds, as well as the derivative at any given point. Second, based on the cause of the increased noise effect, we devised a simple method of noise suppression. Our main objectives are to replace the widely used logarithm function with a customised sigmoid function that is more suited for later image display steps and does not require lightness clipping. To limit information loss, the sigmoid function is utilised. Our introduction begins with a brief overview of picture capturing, the human visual framework, and retinex. The difficulties of nighttime image acquisition, as well as their remedies, are also highlighted. The introduction also includes the goals for improving the image. Each paper examines the various augmentation tactics used, as well as their advantages and disadvantages. The third section informs us about the numerous image enhancement techniques that are now in use. It includes details on multi-scale retinex technology. The proposed method for our study is described in the next section. This part goes over the specifics of the sigmoid function, as well as the necessary illustrations and arithmetic calculations. The specifics of noise reduction and high-light preservation solutions are also covered in detail. The framework's preliminary architecture and algorithm are discussed in the next part, as well as the mechanics of implementing the proposed ways. The conclusion, as well as the future scope, are found in the final section. The bibliography can be found in the last section.

II. RELATED WORK

Night-time image development has progressed at a dizzying speed during the last few decades. There have been various suggestions for improving visual quality at night. A recent work titled MSR improvement for night-time image enhancement [13] employed the MSR approach. The augmentation was discovered to be reliant on the fundamental MSR technique, with some improvisation. The MSR concept was introduced with one modification: the log was substituted with a sigmoid function that was tuned to minimise information loss. The bright channel was used to get an initial transmission estimate in [14], while the dark channel was used as a supplementary channel to rectify erroneous transmission estimates from the light channel. This technique had a disadvantage in terms of the cost of computation complexity. The guided filter and retinex method, which was used as an edge-preserving smoothing operator in [15], were used to perform gamma correction. This method, however, resulted in uneven illumination and unstable artificial light sources.

In [16], a fuzzy dissimilarity histogram based on fuzzy contextual information of the images was used to capture the neighbourhood characteristics of a pixel using a fuzzy similarity index and fuzzy contrast factor. The fuzzy dissimilarity histogram is a new histogram that makes use of each pixel's fuzzy contrast factor (FDH). A cumulative distribution function was generated with standardised values of an FDH and used as a transfer function to obtain the contrast enhanced image. Although the technique provided good contrast enhancement, it was unable to preserve the image's intrinsic qualities. Low-light image enhancement using variational optimization-based Retinex model proposed an enhancement method in which the initial illumination is estimated first, and then the gamma corrected version is used to constrain the illumination component using the variational-optimization-based Retinex algorithm. The reflectance and illumination components were then separated using iterative variational-based minimization. To restore the colour component, the estimated reflectance component's colour was assigned using the input RGB colour channels. To characterise and evaluate digital images using fuzzy statistics, researchers employed a modified methodology termed Brightness Preserving Dynamic Fuzzy Histogram Equalization (BPDFHE) in [18], [19]. The downside of this procedure was that it resulted in data loss. [20] outlines a ground-breaking technique to image enhancement that permits an image's quality to be improved under certain conditions. It was developed in response to a weakness in previous methods. It merged two techniques, retinex and guided image filtering, to develop a new method that could surpass both. The technique, however, did not improve the visual quality. Color picture improvement with Retinex algorithm [21], a weighted variational model for estimating lighting from an observed image using a retinex-based technique, was published recently. These results validated the proposed model's and algorithm's efficacy. When compared to earlier variational tactics, this strategy yielded equivalent or superior results on both subjective and objective assessments. The most significant flaw was that the computing efficiency was just approximative.

III. PROPOSED METHODOLOGY

Some of the disadvantages of the original MSR approach are as follows: 1) It looks that data was lost during the clipping process, particularly in areas where the light between the pixels is uneven. 2)Amplification of noise: The Retinex increases the brightness difference between neighbouring pixels, amplifying the noise that is often present in nighttime shots compared to daytime images. As a result, we provide a custom-designed Sigmoid function that is well limited and compresses lightness between pixels within that bound. As a result, there is no need for cutting and no data loss. It's a monotonic rising function with an easily changeable shape. Simple methods are also utilised to reduce the increased noise effect and retain adequately lit image sections.

The sigmoid function is a continuous nonlinear activation function. The word "sigmoid" comes from the shape of the function, which resembles a "S." A sigmoid function is a real-valued, differentiable function having a nonnegative or positive bell-shaped first derivative. In a variety of image processing research, it has been used. With x as the input, the sigmoid function is as follows:

$$Sig\left(u\right)=\frac{1}{1+e^{-u}} \qquad (1)$$

The function is limited and increases monotonically, just like a logarithm. It has to be changed to have a 0 to 1 output range, an appropriate derivative and function value when u = 1, and a logarithm-like form. This enhancement strategy is a point process that is performed directly on each pixel of an image, regardless of the other pixels in that image, to alter the dynamic range of that image. The correct sigmoid function to use is

$$Sig\left(u\right)=\frac{1}{1+e^{-ku+b+c}}\cdot\frac{1}{c+1} \qquad (2)$$

Retinex gets more sensitive as k increases. The sigmoid travels through the points (0,0) and (1,0.5) and terminates at $(+\infty,1)$ thanks to the parameters b and c.

The amount of noise in your image is reduced when you shoot at a lower ISO. When the ISO is increased, the camera's sensor is directed to merge pixels together to catch lighter. As a result of the clustering effect, the image may appear grainy and noisy. The amount of information that can be recovered from this area is severely limited when the surrounding brightness is extremely low, because it is full of noise pixels and is regularly destroyed by the compression method used to preserve pictures/videos. As a result, we use the Weight factor to determine how much of the retinex result will be included in the final image in low-light areas of the image. The retinex result may be worthless in very low-light conditions; the W1 should be near to 0. W1 should be close to 1 in other places. We use a weighting factor of

$$W_m^1\left(u,v\right)=1-\left(1-L_m\left(u,v\right)\right)^{20} \qquad (3)$$

Where

$$L_m(u,v) = S_m(u,v) * M_n(u,v) \quad (4)$$

A highlight is a bright white with a saturation close to zero and the original object's hue. The retinex technique, in reality, has a tendency to redistribute overall pixel lightness around 0.5. In low-light circumstances, this 'greyish' appearance works nicely, but not so well in brighter ones. As a result, we use to distinguish between locations with insufficient lighting and those with sufficient lighting.

$$H_m(u,v) = \max_{m=1,2,3} L_m(u,v) \quad (5)$$

In low-light conditions, all three colour bands' brightness levels will be quite low to estimate the current pixel's illumination degree. We only need to use the lightest of the three bands to describe the lighting quality of this site. To apply the illumination intensity, a new weight component is created.

$$W_m^2(u,v) = 1 - \left[H_m(u,v)\right]^{0.5} \quad (6)$$

Finally, we multiply the entire weight by the following formula to obtain the total weight:

$$W_m(u,v) = W_m^1(u,v).W_m^2(u,v) \quad (7)$$

and the final equation of our proposed MSRBI:

$$I_m(u,v) = F_m(u,v).W_m(u,v) + S_m(u,v).\left(1 - W_m(u,v)\right) \quad (8)$$

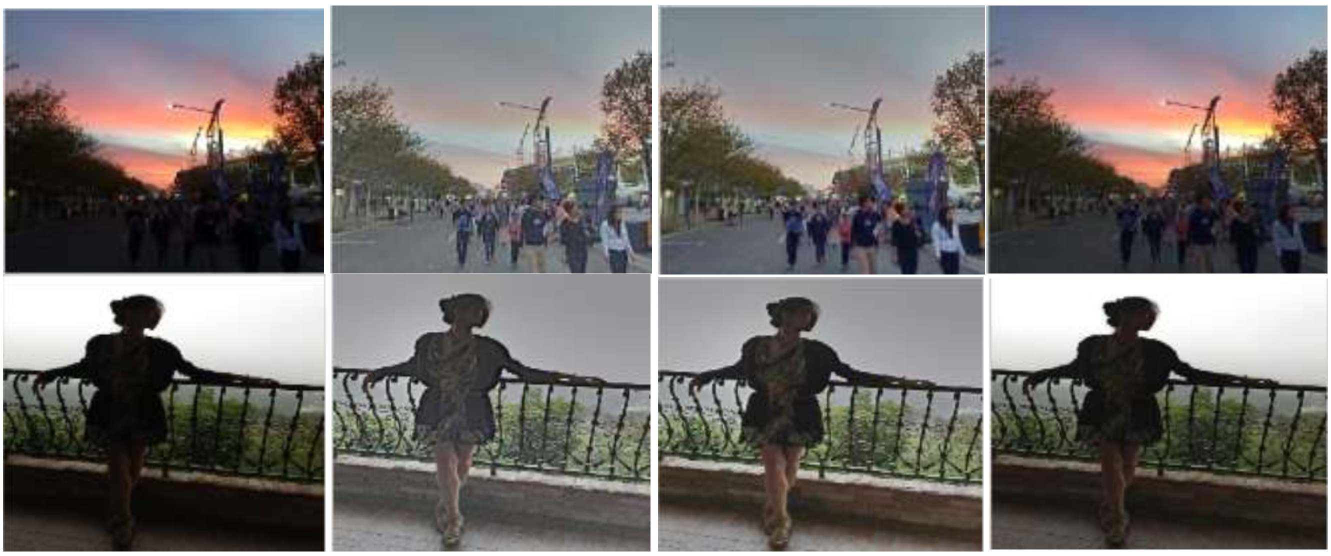
Where

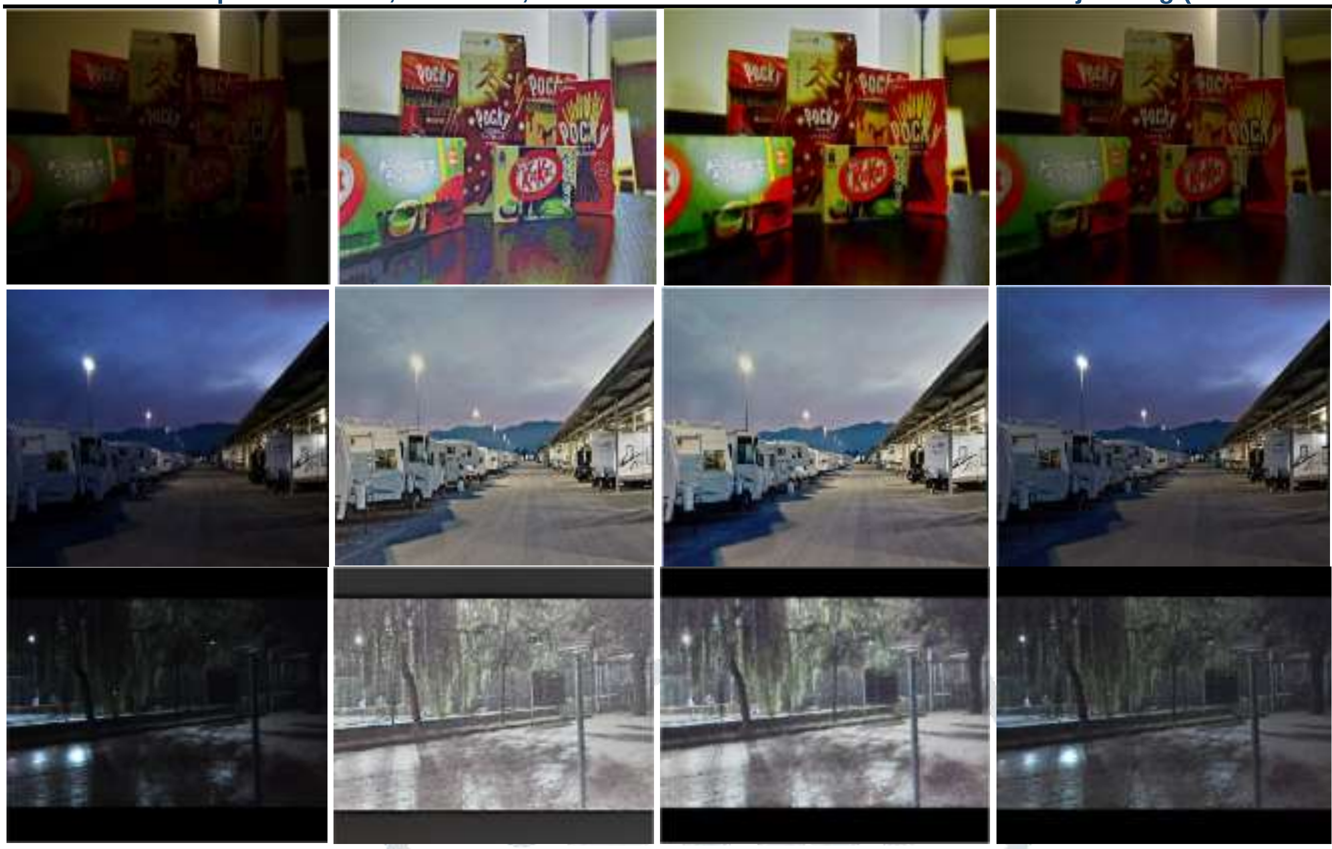
$$F_m(u,v) = \sum_{n=1}^{N} W_n\left\{Sig\left(S_m(u,v)\right) - Sig\left(S_m(u,v) * M_n(u,v)\right)\right\} \quad (9)$$

A good highlight-preserving transformation should not convert a saturation-nonzero pixel to a saturation-zero pixel. Highlight preservation is necessary for colour image enhancement. It's possible that distortion will occur if the colour isn't preserved. The hue of a pixel in the section before the conversion and the hue of the same pixel after the conversion must be the same for a hue/highlight preserving conversion. The purpose of this section is to provide a universal contrast enhancement transformation that preserves highlights. The main purpose is to improve night-time photographs using MSRBI. An image is employed as the input in the proposed technique, on which our system can function and deliver the increased output. In this case, we can utilise either an RGB (colour image) or a gray scale image. We worked on all three channels for colour photos: r-channel, g-channel, and b-channel. Another way to work with colour images is to convert an RGB image to an HSI image, then use the I-channel to improve it before converting it back to an RGB image. We used the RGB picture and RGB channel for the colour image. The increased image output with Retinex necessitates illumination. Without knowing the illuminance state and/or the source of illumination, determining the lighting of an image is exceedingly difficult. As a result, the illumination in MSRBI is the input image's smooth form.

IV. RESULTS AND DISCUSSION

The outcomes of several approaches, as well as MSRBI, our noise suppression technique, and our highlight preservation approach, are displayed here. In these data, the sigmoid function is employed to indicate the retinex. The noise suppression procedure can dramatically reduce noise in dark conditions. Figure 1 displays the results of various algorithms, such as closest and bicubic, our technique with and without noise suppression, and our method with and without highlight reserving. Experiments show that our framework can maintain areas with average or intense lighting while suppressing noise speckles in extreme low light areas when applied to nighttime photos.





a) b) c) d)

Figure 1: a) Input Image b) Nearest c) Bicubic d) Proposed Method

As shown in Table 1 level 2 had a better outcome than the other levels, as seen in Table 1. As a result, in all of our experiments, we chose level 2. PSNR, RMSE, and SSIM are the quantitative measurements shown in Table 1 for improving imaging. Image quality is increased by higher PSNR, SSIM, and lower RMSE.

Table 1: Comparative analysis of Existing and Proposed method

Images	Methods	Level 0			Level 1			Level 2		
		PSNR	SSIM	RMSE	PSNR	SSIM	RMSE	PSNR	SSIM	RMSE
Image1	Nearest	60.310	0.991	0.246	61.856	0.994	0.205	71.591	0.999	0.067
	Bicubic	60.890	0.992	0.230	62.451	0.994	0.192	72.18	0.999	0.062
	Proposed	60.987	0.992	0.227	62.535	0.994	0.190	**72.29**	**0.999**	**0.061**
Image 2	Nearest	59.968	0.988	0.287	59.886	0.991	0.258	72.494	0.999	0.060
	Bicubic	58.962	0.988	0.287	58.819	0.990	0.260	72.875	0.999	0.057
	Proposed	59.040	0.988	0.284	59.893	0.991	0.258	**72.94**	**0.999**	**0.057**
Image 3	Nearest	55.269	0.973	0.439	58.180	0.985	0.314	68.338	0.998	0.097
	Bicubic	55.895	0.976	0.409	58.819	0.987	0.292	68.997	0.998	0.090
	Proposed	55.923	0.976	0.407	58.814	0.987	0.292	**69.014**	**0.998**	**0.090**
Image 4	Nearest	58.418	0.986	0.305	59.006	0.988	0.285	70.972	0.999	0.072
	Bicubic	59.037	0.988	0.284	59.653	0.989	0.265	71.569	0.999	0.067
	Proposed	59.084	0.988	0.283	59.694	0.989	0.264	**71.643**	**0.999**	**0.066**
Image 5	Nearest	55.784	0.975	0.414	57.378	0.982	0.344	66.663	0.997	0.118
	Bicubic	56.160	0.977	0.396	57.758	0.984	0.330	67.016	0.998	0.113
	Proposed	56.188	0.977	0.395	57.776	0.984	0.329	**67.038**	**0.998**	**0.113**

V. CONCLUSION AND FUTURE SCOPE

We offer an upgraded Retinex framework that compresses rather than clipping the 'extreme' pixels using a proprietary sigmoid function to obtain superior picture enhancing results. As a result, unlike the logarithm approach, it does not necessitate the use of the gain-offset method, which necessitates clipping and causes data loss. The retinex process, in reality, has a propensity to re-distribute overall pixel lightness around 0.5. In low-light circumstances, this 'greyish' appearance works well, but not so well in brighter ones. As a result, the characteristic lighting zones that are subjected to the process are preserved by our technology. Furthermore, the retinex procedure should only have a limited effect in a specific area with very low light. As a result, a weight factor is used, which reduces apparent noise magnification. In the proposed method, we basically addressed using the MSRBI approach with the sigmoid function to build an accurate image. The proposed method is utilised to eliminate the "halo effect," remove noise speckles, improve picture contrast, and restore image features while requiring little effort. In the future, the primary goal is to create an algorithm capable of accomplishing the tough task of updating night-time photographs.

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