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An Improved Retinex Method for Low Light Image Enhancement

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Abstract- Enhancement of low-light image is difficult because it must account for not just brightness recovery but also more sophisticated concerns such as colour distortion and noise that are often hidden in dark. Increasing the brightness of a low-light image, even slightly, can make these artefacts more noticeable. Image enhancement in low-light circumstance from the surveillance system plays a very important role for the security purpose. This is an active research topic, where many algorithms are proposed for magnifying the intensity of dark images. To overcome this issue a unique end-to-end attention-guided technique based on retinex is proposed. Here many effective image enhancement methods are ground on retinex theory. Subsequently diverse algorithms are used such as single scale retinex (SSR), multiscale retinex (MSR), multiscale retinex with color restoration (MSRCR) models. $\boldsymbol{L}^*\boldsymbol{a}^*\boldsymbol{b}^*$ color space model is applied with retinex algorithm. To boost the quality and brightness of image; gamma correction with multiple values are used before applying Improved Multi Scale Retinex with CIELAB color (IMSRLab) on image. Extensive testing on standard LOL datasets demonstrates that our method is capable of delivering high fidelity enhancement outcomes for lowlight images, and that it outperforms existing state-of-the-art methods both statistically and visually. These findings were gleaned from comparisons of the two methods using the LOL datasets.

Keywords— *low / dark light image, single scale retinex, surveillance system, multiscale retinex.*

I. Introduction

Videos captured from the surveillance systems are of poor visibility, like in rain, fog, smoke, or at dawn. Because of the extreme drop in contrast, these scenarios drastically restrict the range and efficacy of imaging equipment. Digital images utilised in modern imaging or vision-related applications should be of high quality in order for these programs to perform their functions effectively [1]. Poor-light effect, low contrast, and incorrect colours characterise images acquired in an insufficient lighting condition [2]. Since a result, capturing high-quality images in such conditions is difficult, as low-light impact might reduce the performance of various image processing applications [3, 4]. Furthermore, such images often have large black patches with little visibility [5]. Low-light photographs are images taken at night, with uneven lighting, in a shaded environment, an overall gloomy look, and a hazy appearance [6], with examples of images taken under such situations displayed in Figure 1.

Figure 1- Various types of low-light images. (a) and (e) cloudy; (b) uneven illumination; (c) and (d) night time; (f) daybreak and nightfall.

Edwin Land, an American physicist, believed that throughout the visual information transmission filter, humanity's visual system continued to analyse the information, removing its light source level and non-uniform irradiation, among other questionable aspects, and only retaining the information. This inherent information detailing object substantive property will be conveyed to the cerebral cortex, and following more complicated information processing, human vision will emerge. Edwin Land introduced the Retinex colour theory

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for the very first time in [1] based on this insight. As per the Retinex theory, the current element colour may be established by comparing the mean light and shadow relations among the image's different components and applying adjustments to each part in the image, which is known as the long-established global retinex algorithm.

Retinex method has been a hot topic in image improvement research. The Retinex algorithm's basic concept is to distinguish light from reflectance. According to the theory, the information that can be obtained about an object is determined by the reflection coefficient and the intensity of the light around it. The intensity of the light determines the dynamic range of the pixels in the image, while the reflection coefficient helps determine the inherent attribute of the object. The method of dividing an image into two parts is called the reflection image and the brightness image. The first one eliminates the influence of light, while the second one retains the object's inherent attributes. following formula is used to construct Retinex

$$S = R \times L \qquad (1)$$

An input image is represented by the bivariate function S. The original image consists of two image effects; lighting L and reflectance R, which are separated to create the retinex effect. Many efforts have been made to calculate the illumination image quantitatively. Figure 2 depicts the retinex hypothesis with an image creation model. Retinex algorithms are categorized as SSR, MSR, MSR with colour restoration, and so on, depending on how the illumination is estimated.

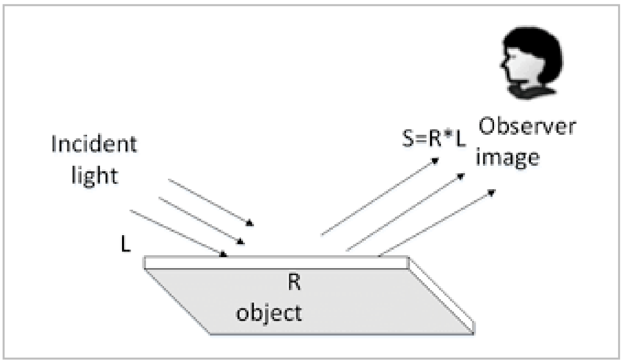

Figure 2- Image formation model

Due to illumination fluctuations, human insight succeeds at building a visual display with realistic colour and features over a broad range of photometric levels. Figure 3 depicts how an observer views an item when light is direct on it. To accurately depict the directly seen scene, the captured images must undergo certain processing, like restoration, de-blurring, and enhancement, in arrangements to keep up the recorded image towards the observed image. In the field of image processing, including face biometrics and object tracking, improving the quality of image is a critical preprocessing step. Image enhancement aims to increase viewers' capacity to comprehend or perceive information in images, or present much better contribution for many other computerized image processing approaches.

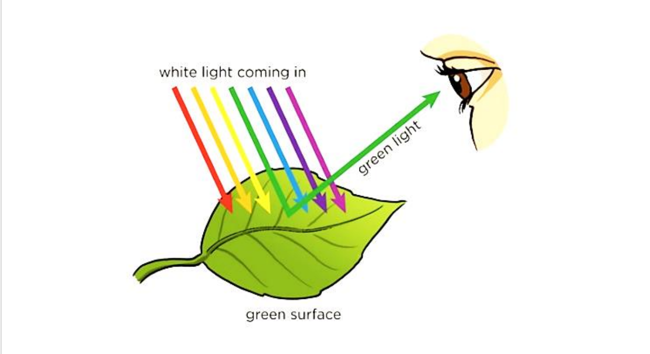

Figure 3- Example of Retinex Theory

The estimate and normalising of illumination are the two primary processes in the Retinex approach. As previously stated from input image I the illumination L is calculated which is clean form of image I. After the estimation is finished, the gap between the input image's logarithms and the predicted illumination is used to normalise the illumination. As illumination anomalies such as projected shadow contradict the premise that light slowly fluctuates, smoothing should be done in particular among pixels with homogenous illumination. Several methods are used to reduce the effect of the incident image, to retain the essential reflection attribute image of the object. Retinex method has three main techniques, SSR, MSR and MSRCR. The algorithms for these methods are discussed along with the proposed method IMSRLab.

The following is a summary of our contributions:

(1) For low-light images improvement, a unique self-regularized technique is suggested that, inspired by the HSV colour space, retains all colours while only integrating Retinex into brightness. Use of gamma correction in pre-processing step to intensify the quality of image.

(2) Furthermore, to test the performance of this system on the publicly available LOL dataset.

(3) To analyse the performance of a proposed improved Retinex model and performing Extensive tests to illustrate the efficacy of our system and its advantages above current best practises.

This work is organized as follows: First section starts with an introduction of retinex theory and the problems occurred during the low light image enhancement technique, section 2 is a literature survey, description of the proposed system is explained in section 3, section 4 is findings and discussion, and section 5 is conclusion.

II. LIterature Survey

The gap was higher when the images had a low visibility condition. The difficulty is that there is frequently a disparity between the digital form of a recorded image and the representation in the vision of the viewer. This is something that needs to be addressed. It's almost impractical to perform exact match of observed scene and previously stored image perfectly, even under ideal recording settings and with the greatest recording equipment. This is due to the fact that both the recording and imaging equipment add artefacts into the acquired images. Blurring owing to the camera lens and capturing system characteristics, the camera's restricted dynamic range, and the SNR due to the device electronics' thermal properties are all examples of these artefacts.

As stated by retinex theory in [1] one can analyse an image by analysing its reflectance and illumination separately.. Land E H et al in [1] explains the retinex algorithm, and describe the concept of how human visual system change the object colour and brightness in different lights condition and view from various angle. According to author retinex algorithm can establish a balance in colour consistency gradation, edge enhancement and dynamic range compression, allowing it to be utilised for automated enhancement of many types of images. The technique, however, is based on experimental data and does not use a unitary mathematical model. SSR [2-3], MSR [4], MSRCR [7], and more enhanced retinex algorithms arose and gained broad use. All of these traditional Retinex algorithms work by smoothing the original image using a Gauss model with specific attributes and extracting the image background as accurately as practicable using various methods.

To achieve natural reflection and lighting, a variety of options are given; In [8] Wang et al. created a naturalness preserved enhancement (NPE) method to maintain the image's authentic appearance while simultaneously improving its quality. A lightness order error measure was used in order to achieve a natural look, and a bright-pass filter was put into play so that a picture could be broken down into its reflectance and illumination components.. To establish a balance between details and naturalness, a bi-log transformation was also designed. Fu et al. [9] performed combination of adaptive histogram equalisation and decomposed illumination which is obtained by using sigmoid function.

To address this issue, Kimmel presented the variant Retinex model [15], which employs extra image mathematical calculations as model constraints. For instance, [16] enhanced the detail-preserving behaviour of the reflectance by introducing a sparsity prior and a quadratic fidelity prior; [17] increased visual fidelity by introducing a regularised total variation term; and [18] assured the staircase impact suppression ability by incorporating the Gaussian curvature regularisation and the first-order differential term. Because the variation Retinex-based models' minimization problem is QP in terms of the unknown image, and overall computing consumption is usually determined by model complexity, computational complexity is surrendered as a trade-off.

A low-light image enhancement technique known as LIME is proposed by Guo et al.[21], which takes into account the varying priority of each pixel in the image. They then adjusted the illumination map by taking into account a structural prior. Based on their previous work, Fu et al.[19] propose a weighted variation approach that can retain more information about the reflectance while reducing the noise. In order to improve the noise estimation, Li and colleagues [20] developed a robust model known as the retinex. Unlike the traditional model, this one includes a noise map.

Another technical hint demonstrates its advantage in terms of computing efficiency as compared to other Retinex-based approaches. Dong [11] used an experiment to identify the similarities among the inverted low-light photographs and hazy images, with the goal of removing "haze" from the inverted low-light image. The “haze-free” output was flipped again after "haze" removal to create the improved low-light image. The atmospheric scattering model (ASM) [12] and the DCP-based transmission estimate algorithm [10] are the foundations of Dong's method. Based on this technical hint, [13] revamp the quality by using segmentation and adaptively scene-wise denoising via pre-processing for the DCP-based transmission estimation. The inverted low-light picture improvement paradigm is hard to decipher, and the impact of image quality improvement is uncertain.

Histogram equalisation (HE) is a commonly used approach for improving the dynamic range of a low-light image by changing the histogram [22]. With the use of this procedure only contrast boost, under-exposure and over-exposure are easily produced. As a consequence, the methods used to build HE resulted in HE with a large number of priors. A maximum entropy brightness keeping histogram equalisation method is proposed by Wang et al. [23] for the purpose of selecting a target histogram with the highest entropy below a given mean brightness. To prevent undesired visual degradation, Ibrahim et al. [24] use a brightness preserving dynamic histogram balancing approach that keeps the mean brightness of the input picture within the output image. A one-dimensional Gaussian filter is utilised to polished the input histogram before partitioning it based on its local maximums. Based on advanced dynamic ranges, HE is applied individually to these divisions. Finally, the generated picture is standardised to the mean brightness of the input image. In [25] Lee at el. created two distinct transformation algorithm for the foreground and background using depth information.

Contrast enhancement approach has been frequently utilised to boost the contrast of images that have been poorly lit for many decades. Histogram equalisation and the Retinex hypothesis are the mainstays of traditional approaches. Histogram equalisation is a basic but effective image enhancement technique that works by altering the images histogram to improve contrast, for example, brightness-preserving bi-HE [26].

III. Proposed Work

The concept of the Retinex is an image enhancement method that combines the capabilities of a nonlinear spatial transform and a spectral transform to produce high-quality visual representations. It was developed to compensate for the non-uniform illumination in each image. The method was inspired by the belief that the human vision system is subjective when it comes to perceiving colors. Under varying lighting circumstances, the human visual system ensures that the apparent hue of the goal stays generally consistent. This property aids in the identification of items. Retinex works similar to the human vision system. The estimate of illumination map and that of reflectance map is also important for Retinex-based algorithms. Traditional procedures often provide over/under-enhancement outcomes due to their limited breakdown ability. Learning-based approaches may provide better decomposition results and boost contrast more effectively, but most of them ignore noise. Our network is divided into three subnets that control decomposition, denoising, and contrast enhancement.

A. System Architecture

Figure 4 shows the proposed system flow. System takes LOL image dataset as input after performing preprocessing and resizing on input dataset gamma correlation is applied by setting up several value of gamma. After applying gamma correlation CIELAB color space model is applied on preprocessed image. Then several Retinex based models are applied on images and at the end the proposed improved Multi Scale Retinex with CIELAB color space model is applied to get good quality image. Finally, the performance of different model is compared using Mean, MSE, PSNR, Contrast, Entropy parameters.

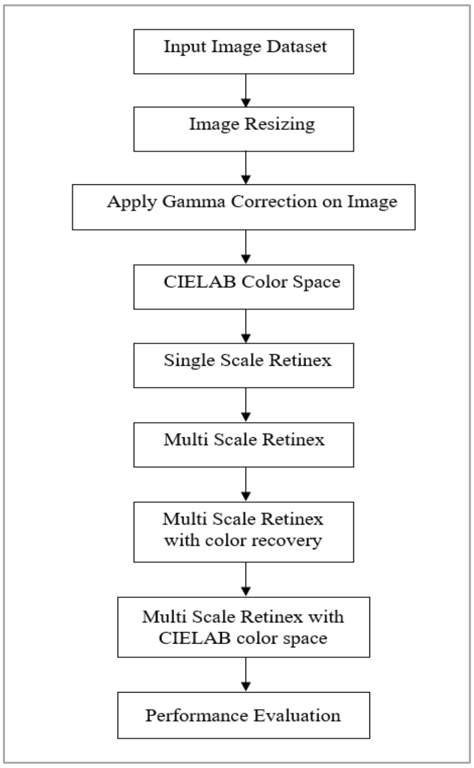

Figure 4- Proposed System Flow

B. Gamma correction

Gamma correction is also referred to by its alternative name, the Power Law Transform. To get started, we need to change the intensity range of our image pixels from [0, 255] to [0, 1.0]. Then, in order to obtain our final gamma-corrected image, we will use the following equation:

$$O = I \wedge (1 / G)$$

Our input image is I, and our gamma value is G. After that, the output image O is rescaled to the range [0, 255].

When the gamma value is less than one, the image will appear darker, and when the gamma value is greater than one, the image will appear brighter. The supplied image will have no impact if the gamma value is set to G=1. We utilised a gamma value scale of 1 to 2.5 here. The results of processing a low-light image with number of gamma values are shown in the following figure.

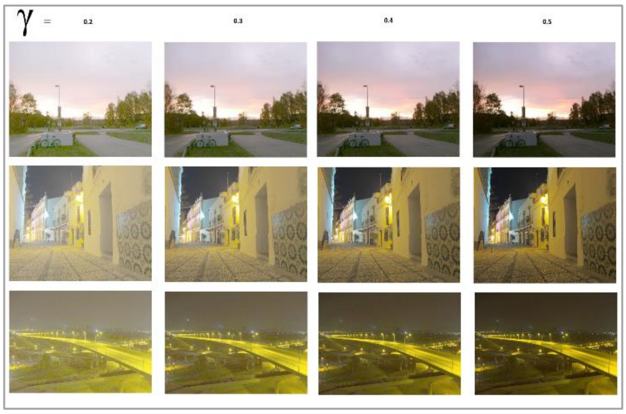

Figure 5- Output of processing a low-light images varying gamma values:

(a) γ =0.2, (b) γ =0.3, (c) γ =0.4, (d) γ =0.5

C. CIELAB Color Space

The International Commission on Illumination (CIELAB) colour space, often known as The International Commission on Illumination has defined $L^*a^*b^*$ as a colour space. It represents colour with three values: L^* for perceived brightness, a^* and b^* for the 4 unique colours of human visual: blue, red, yellow, and green. The colours it depicts are based on the CIE standards observer, which is also an average of the outcomes of colour matching experiments conducted in a lab environment. The three CIELAB coordinates represent the color's lightness position among red and green as (a^* , where negative values specifies green and positive value shows red), and position among yellow and blue (b^* , where negative values specifies blue as well as positive values shows yellow. The $L^*a^*b^*$ model contains three coordinates, which are fully represented in three dimensions as the two-dimensional chromaticity maps fail to capture the whole gamut's complicated geometry. It's also important to note that the visual representations of the whole CIELAB model depicted the plots on the page are just that representations. The monitor will not be able to display the true full gamut colours. The red-green and yellow-blue opponent channels of CIELAB are determined as differences in brightness transformations of cone responses, making it a chromatic value colour space. The eye's nonlinear reaction is modelled by the nonlinear relations for L^*, a^*, and b^*. Moreover, because as uniform changes in parameters in the $L^*a^*b^*$ colour space are intended to the relative perceptual difference between any two $L^*a^*b^*$ colours may be approximated by considering each colour as a point in a three-dimensional space and computing the Euclidean distance between them.

Each colour channel is treated independently in the traditional method to colour image enhancement. These approaches often provide a colour correction effect, although they may sometimes produce colour artefacts that exaggerate colour shifts or lower colour saturation. Unlike typical Retinex algorithms, here the input image is converted from RGB to $L^*a^*b^*$ colour space before applying gain correction to the clean or filtered image. At the end system converts the colours back to RGB. Because the lighting has a low frequency module when it compared to the reflectance. A low-pass filter is used to estimate the illumination by retinex method. Though the Gaussian filter employed in the filtering process would undoubtedly lose certain high-frequency components, image features and edges will be lost, resulting in image distortion.

D. Retinex on a Single Scale (SSR)

In SSR, image is transformed into a logarithmic function, and the illumination layer is a function of a Gauss transform, which subtracts the transform of both the image and the layer to produce the output. In SSR, we'll be working with a low-quality image, and we'll need to improve it. To achieve this, we'll use the surround function to transform the image into an illumination. The method used by the retinex method subtracts the log of discovered illumination from the input image to get the reflectance, and then the result will be upgraded as an enhanced image. This is referred to as SSR, and it only uses one function to determine the lighting. In our study, we used this method to determine the enhanced image's outcomes after gamma correction.

Algorithm:

1. Read the original image
2. Apply gamma correction
3. Take out the numerical matrix of RGB three channels, and convert it into double type.
4. The convolution of each channel is processed by Gauss template.
5. Both the RGB and distorted images are translated into the logarithmic domain, and then the RGB image is subtracted, and then the inverse number is transformed into the real number domain.
6. The image of each channel obtained is stretched linearly, and the processed image is combined with RGB.

SSR can deliver both dynamic range compression and complete rendition at any given time, but not simultaneously. This is because it only uses a single scale to determine the lighting, which limits its ability to provide appropriate results. A new strategy known as MSR has been developed to solve this issue.

E. Multi Scale Retinex (MSR)

MSR mixes the varied characteristics of numerous surround regions to provide an image with a high dynamic range and overall compression. Several surround functions on a single stage are utilised to determine the lighting in MSR. After utilising the convolution procedure to compute the illumination from all distinct scales, one needs calculate their log. Then remove the calculated illumination from the log of image for one scale, and repeat for every computed illumination. Calculate the weighted average of all the findings for each scale to produce the final enhanced image. Multi scale Retinex is the sum of the weighed outputs of multiple SSR scales. This balance is insufficient for SSR, which requires a precise balance of colour accuracy and details. MSR is presented as a solution to this issue. It seeks to process one image using the Gauss filter on several scales, and then weight the images using numerous scales. It's an SSR stack operation.

After improving an image, MSR provides the majority of the information. It is better than SSR, but it can't provide natural appearance of the image. It can provide results that are both dynamic range and complete rendition, though it has a color sensitivity issue. Although MSR is a great tool for improving a greyscale image, it has issues with colour photography. We can't tell if the resulting image is right or wrong after processing it. However, we want Retinex to generate a result in the same manner that a person looks at a view point and adjusts their thinking to find out the specific characteristics of the image in terms of colour and other features. As a result, MSR with colour Restoration was proposed as a way to overcome MSR's limitations (MSRCR).

F. Multi Scale Retinex with color recovery (MSRCR)

After enhancing a greyscale image using MSR, the image may be greyed out in a few locations, which can be global or local. As a result, there was a requirement for a formula that could deal with colour in order to keep the image's colour. Color restoration should retain colour consistency, since this is Retinex's primary goal. Although colour constancy is not perfect in human eye, it should be acceptable in restoration methods. The weights for the three-color channels in the original image are introduced in MSRCR based on their relative intensities. To accomplish the aim, this method employs MSR with the addition that the MSR output is multiplied by the colour restoration function. MSRCR will take an image as input and compute a colour restoration function for it. It is necessary to conduct the MSR operation on the image after calculating the colour restoration function. MSR will then execute a multiplication operation using the calculated colour restoration function as its output. MSRCR adjusts the result of MSR according to a certain proportion to restore the original proportion value, specifically by introducing the colour recovery factor C, due to the difference in the contrast between the MSR and SSR images, this feature was used to fix the color distortion caused by the effect of contrast enhancement.
It is a superior technique than prior image enhancing systems, however this approach is difficult as it requires control over the degree of colour restoration and offset value. Gain and offset values in MSRCR may result in information loss; therefore, it is essential to determine how to obtain gain and offset in the restoration process so that MSRCR produces useful results.

G. Improved Multi Scale Retinex with CIELAB color space (IMSRLab)

Image enhancing techniques based on Retinex have been extensively employed. Over-enhancement and unnaturalness are unavoidable since many Retinex-based algorithms eliminate light and view reflection as enhancement. Following the illumination and reflectance decomposition, a straightforward and compelling post-processing approach for lighting modification is used to improve the outcome and make it more realistic.

The CIELAB is 3D and spans the entire range of human colour insights. The model is based on the opponent colour adversary of human vision, where red-green colour produces an adversary pair and blue-yellow creates an adversary pair. L^*, sometimes known as "L-star," is a brightness scale in which black equals 0 and white equals 100. A negative number represents green, and a positive number represents red, the a* axis is oriented relative to the opposing green and red hues. On the b* axis, the blue–yellow opponents are displayed, with negative numbers indicating blue and positive ones indicating yellow. The MSRCR technique may improve the image overall, however colour cast and halo effect will appear in areas with extremely high contrast.
The following flaws exist in the original MSRCR algorithm:
1. Each scale's weighting components are fixed values, ignoring the original image's rich gradient information.
2. The classic Retinex algorithm assumes that space lighting changes slowly, which is extremely different from the real world, where image brightness varies constantly.
3. The Gaussian filter performs poorly in terms of edge preservation.

The suggested solution overcomes these limitations and can handle a wide variety of image types, including high dynamic range (HDR) and non-uniform illumination images.

To extract the backdrop in this method, first capture either successive image frames from the movie or the similar or same image. Then, using a multi-scale gauss mask filter, it applies filtering to all of these images so that effective lighting may be obtained for all of them. Use the minimal approach in after applying the mask to the similar image images and blending the final outputs from the filtering step. Then, for each unique input image, you'll receive a unique output. Use the maximum approach on all distinct outputs to create a homogeneous backdrop image by blending them all together. After you complete the procedure, the result will be in such a way that the image will be illuminated. To achieve the output result, which is an image with better quality, restore the image by using $L^* a^* b^*$ coordinates.

There are three key phases in the proposed algorithm:
1. Using a multi-scale Gauss mask, remove the background using various scale and variance settings.

2. The maximum method, which takes the highest value in the result from all the specified inputs, can be used to blend the lighting of neighbouring image frames..
3. Apply image enhancement techniques to the input image, taking into account the calculated illumination of the input image using $L^{*}a^{*}b^{*}$ coordinates.

Following this approach, it is possible to conclude that an increase in the accuracy of image background extraction will result in significantly better image enhancement. The assessment of lighting of the image and its backdrop is the emphasis of this technique. After estimating the image's lighting, it simply employs Retinex's fundamental approach to locate the improved visual representation in the Retinex-processed output.

IV. Result and Discussion

A. Experimental Setup

On a system with an Intel Core i5, 6^{th} generation, Windows 10 (64 bit) machine with 8 GB of RAM and 512 GB SSD, experimental methods are developed in this project used Anaconda Jupiter Notebook tools, and Python as technology. Data normalization was applied to the training images.

B. Description of the Dataset

The LOL dataset is used, and it is a real dataset with 485 image pairs used for training and 15 pairs used for testing.. The dataset contains a variety of scenarios at a resolution of 600400 pixels. As the new training dataset, we chose 234 image pairings from the LOL dataset's training dataset, as well as 15 images from the LOL dataset's testing dataset and another 8 images from the LOL dataset [6].

C. Performance Parameters

Mean, Peak Signal to Noise Ratio (PSNR), MSE, Contrast, Entropy are used as the performance metrics in this section. Following are the formulas used for performance metrics calculations;

$$MSE = \frac{\sum_{M,N}[I_1(m,n) - I_2(m,n)]^2}{M * N}$$

$$PSNR = 10\, log_{10}\left(\frac{R^2}{MSE}\right)$$

$$E(I) = -\sum_{k=0}^{L-1} p(k)\, log_2\,(p(k))$$

Where R be the maximum fluctuation in the input image. $p(k)$ be the a measure of the likelihood that the value k will be found in the image I.

D. Visual Quality Comparison

Here we conduct experiments and analyses to demonstrate the efficacy of the proposed IMSRLab approach. We experimented with images under various lighting settings. The images were taken from the LOL collection. Different fog/haze remote sensing images are used to evaluate the suggested technique. We first demonstrate the performance of existing methods SSR, MSR, and MSRCR on the original image and on the proposed IMSRLab algorithm, and then propose a set of quantitative metrics to evaluate the enhancement algorithms, including mean, MSE, PSNR, contrast, and information entropy.
In order to demonstrate the efficacy of the strategy that has been developed, tests are performed on photographs with various lighting conditions. The suggested IMSRLab method produces the best results, as illustrated in Figure.6's image findings. As can be observed, the SSR method's brightness enhancement impact is restricted, but the MSR approach over-enhances the image, resulting in the loss of certain features in the brighter region, increased noise, and a noticeable halo at the step edge. MSRCR enhances brightness while preserving colour when compared to SSR and MSR algorithms. However, the improved image's contrast is modest, and certain features are lost. Furthermore, MSRCR has the most severe halo effects. The suggested IMSRLab method adaptively enhances local brightness and contrast, successfully enhancing the dark region while maintaining the object area's features. In terms of brightness enhancement, the suggested approach is successful, and the boosted images are the most natural.

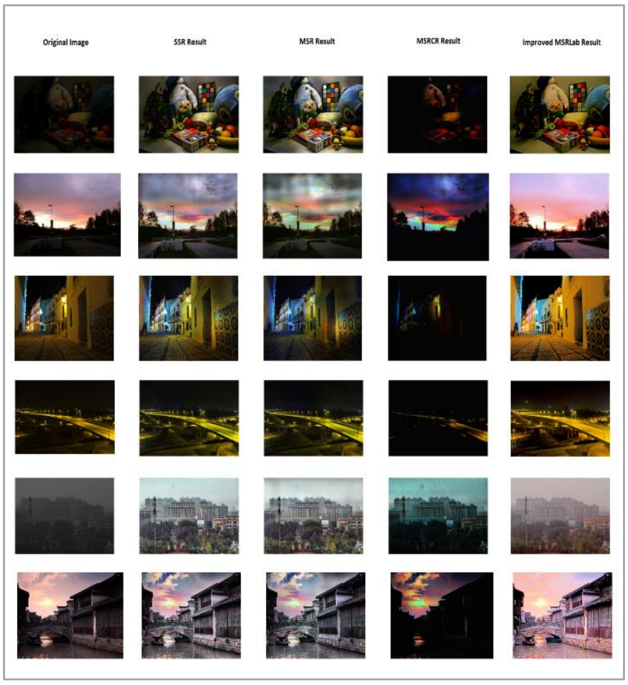

Figure 6. Visual contrasts between various approaches SSR [18], MSR [11], MSRCR [22] and Improved MSR Lab Results.

In order to demonstrate that the algorithm is applicable, the paper uses the LOL Dataset, which consists of six images, of a low-light image, as depicted in Figure 1 as the original image. Figure 6 displays the results of the SSR algorithm, the MSR algorithm, the MSRCR algorithm, and the proposed IMSRLab algorithm, along with the Mean, MSE, PSNR, Contract, and Entropy readings that were obtained. The paper concludes that the algorithm is applicable are shown in Table 2.

Table 1. The five objective measures of the base image and the improved versions produced by various algorithms.

Image Reference	Method	Mean	MSE	PSNR	Contrast	Entropy
[1]	Original	15	24.15	17.63	114	5.22
	SSR	59.74	54.82	17.56	132	7.28
	MSR	69.42	60.96	17.58	133	7.47
	MSRCR	11.78	55.49	17.67	2	3.43
	IMSRLab	55.15	28.79	18.54	124	7.79
[2]	Original	93.42	76.44	17.73	8	7.12
	SSR	99.38	68.49	17.61	15	7.64
	MSR	66.35	67.29	17.58	18	7.62
	MSRCR	44.2	92.33	17.6	6	6.2
	IMSRLab	137.23	53.03	18.66	21	7.31
[3]	Original	45.66	46.6	17.56	18	6.89
	SSR	60.25	53.06	17.54	28	7.27
	MSR	47.6	46.38	17.53	49	6.91
	MSRCR	10.29	72.18	17.65	43	2.9
	IMSRLab	78	27.23	18.66	41	7.18
[4]	Original	24.73	40.8	17.63	43	5.74
	SSR	36.58	45.9	17.6	100	6.27
	MSR	33.79	44.39	17.59	102	6.22
	MSRCR	10.32	58.81	17.67	76	2.22
	IMSRLab	43.13	30.39	18.68	98	7.44
[5]	Original	58.94	30.2	17.45	9	5.95
	SSR	133.39	65.43	17.95	16	7.7
	MSR	128.67	64.35	17.85	19	7.77
	MSRCR	73.31	65.89	17.56	7	7.31
	IMSRLab	123.3	52.25	18.53	18	7.37
[6]	Original	78.89	74.61	17.77	10	7.48
	SSR	103.11	64.9	17.65	11	7.86
	MSR	97.67	64.26	17.59	6	7.81
	MSRCR	31.73	74.18	17.65	5	5
	IMSRLab	143.27	52.76	18.2	21	7.75

Table 2. The average of (6 test images) five quantitative metrics of the novel image and the enhancement results of the various algorithms.

Method	Mean	MSE ↓	PSNR ↑	Contrast ↑	Entropy ↑
Original	52.77	48.8	17.62	33.66	7.35
SSR	82.07	58.76	17.65	51.33	7.33
MSR	73.91	57.93	17.62	53.5	7.30
MSRCR	30.27	58.29	17.63	25.16	3.19
IMSRLab	96.68	43.01	18.54	53.83	7.47

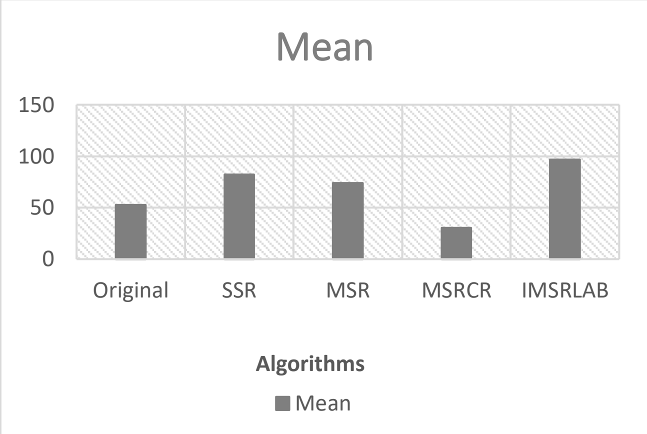

Figure 6- Mean comparison of algorithms

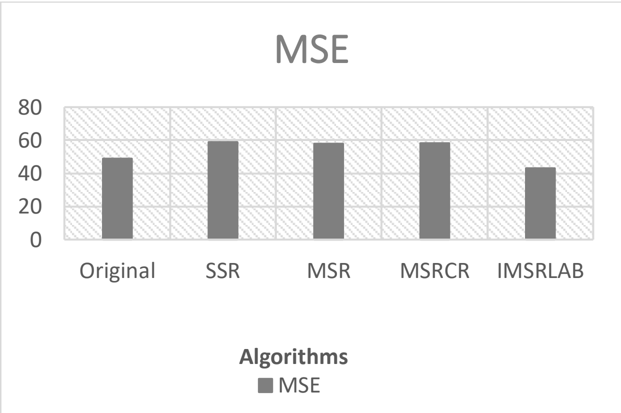

Figure 7- MSE comparison of algorithms

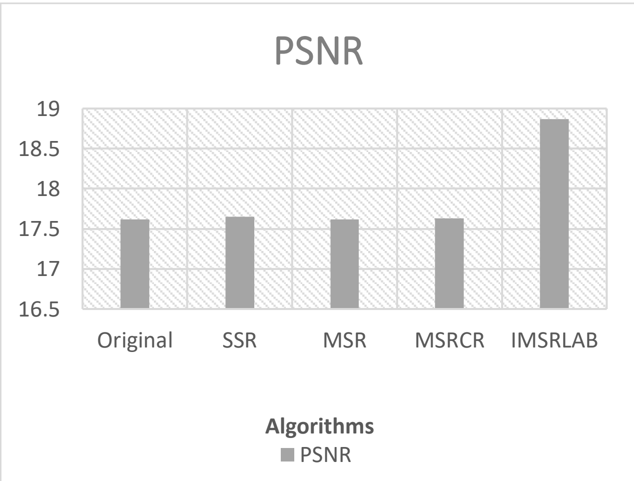

Figure 8- PSNR comparison of algorithms

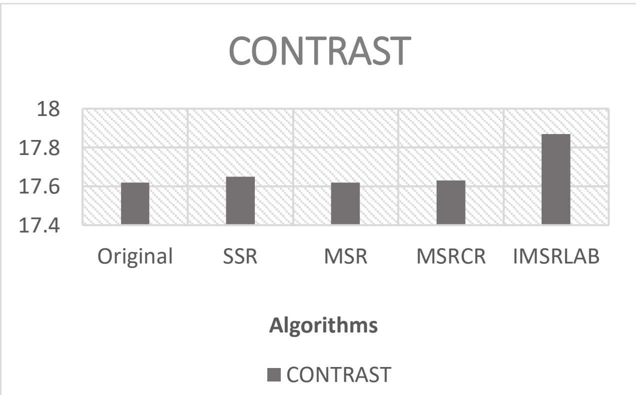

Figure 9- Contrast comparison of algorithms

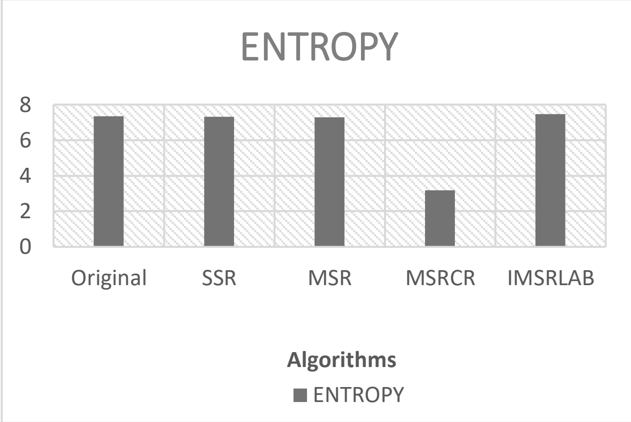

Figure 10- Entropy comparison of algorithms

Figure 6 demonstrates mean comparison graph of algorithms, Figure 7 shows the MSE comparison of algorithm; lower the MSE higher the efficiency of algorithm. SSR algorithm has MSE of 58.76 while the proposed system has lowest MSE which is 43.01. The Figure 8 shows the PSNR comparison of algorithm, PSNR of proposed method is 18.54 which is best compare to all other algorithms. Figure 9 and Figure 10 shows the contrast and entropy graph comparison of algorithms respectively. The image improved by the proposed technique has the highest information entropy, and contrast indicating that it contains the greatest detail information, as shown in Table 2. The image improved by this paper's suggested method has a decent quality, according to testing. It also doesn't have any colour distortion, which is more in line with human vision.

The PSNR scores of different approaches on the LOL dataset is compared and shown in Table 3. Ours system shows better PSNR compare to similar methods.

Table 3. PSNR comparison with similar system

Method	PSNR ↑
Retinex-Net [6]	16.77
LIME [21]	17.18
EnlightenGAN [14]	17.48
Ours	18.54

V. Conclusion

Retinex theory and Retinex based algorithms are discussed. Firstly, introduced Retinex based algorithm is SSR. One scale is used for surround function, and one image can be compressed for all rendition or dynamic reach. MSR algorithm is developed to provide better results. It computes lighting using various scales for the gauss function and provides entire rendition and dynamic reach compression in the image output. Color images are dealt with using MSRCR. It restores the image's colour using the colour restoration feature. Gain-offset is also used to obtain the colour of the output to be the same as the input. All of these Retinex-based techniques are distinct from one another, and each has its own distinct benefit a method for image enhancement that can be chosen based on the application.

When dealing with low-light photographs, IMSRLab is a superior option since it can handle both too little and too much intensity and can improve images with little pixel data loss. The results of the experiments showed that the suggested method could not only suppress halo and colour distortion, but also produce excellent results in detail enhancement and colour integrity. The proposed method was judged to be competitive when measured against the most recent and cutting-edge algorithmic developments. In upcoming research,, it will be possible to increase the algorithm's real-time performance and do practical application research.

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