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# Low-Light Image Enhancement Using Multi-Exposure Sequence Generation And Image Fusion

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***Abstract***

*Image Enhancement is one of the domains in computer vision with prime importance in real-life applications. Images having poor visual quality and visual defects require enhancement to capture the details in an image. This paper proposes a novel fusion-based method for image enhancement of low light images having non-uniform illumination. The methodology works on the estimation and improvement of the V channel of an image in the HSV model. It estimates several contrast based derivatives of V channel and then fuses them to get the enhanced image with desired features. The proposed approach improves the overall contrast and brightness of images. This approach preserves the details and naturalness of the image. Quantitative and visual analysis of the proposed method validates its performance.*

***Keywords:*** *Image Enhancement, Fusion, Low Light Images*

## 1 Introduction:

Low light images are those images that contain many dark regions and non-uniform illumination. Due to low light environment, these images often have multiple under-exposed regions and over-exposed regions in the images. These images lack detail preservation of the scene of the image and have poor contrast. The underexposed areas in the image contain useful information that is not adequately illuminated and thus requires enhancement. The enhancement of such images is, therefore, essential to extract useful details from them. Image enhancement is the process of improving the visual appearance of the image to restore and preserve the details in an image with precision while maintaining the naturalness of the image. Image enhancement finds applications in many fields. It is used in security systems, aerial imaging, medical sciences like ultrasound and MRI, space exploration in the form of satellite imaging, geology etc.

Some of the traditional and most prominent methods of image enhancement include Histogram Equalization (HE) [1] which enhances contrast of images by mapping images using stretched histograms. This technique has various modified versions. Abdullah et al. [2] proposed the concept of Dynamic Histogram Equalisation (DHE) wherein division of the image histogram is done using local minima as the basis. This ensures the proportionality between dynamic output range and input image. Parihar and Verma [3] presented Dynamic Histogram Equalisation (DHE) as an entropy-based optimal division of histogram. However, all these techniques are not completely flawless as they fail sometimes and cause over or under enhancement in images, halo effects and other defects.

Researchers have evolved many neural network based approaches for image enhancement. Shen et al. [4] proposed a deep convolutional neural network model based on Retinex theory for image enhancement which works by creating a mapping between dark and bright images. Gharbi et al. [5] also proposed an image enhancement approach based on neural network architecture, trained using local affine color transformations in a bilateral space. It shows high performance in mobile image processing. Lore et al. [6] proposed a lowlight image enhancement approach based on auto-encoders, which used SSDA (Stack Sparse Denoising Auto-encoder) architecture for calculating relation between an input image and the enhanced image.

Fusion is a relatively less explored domain in image processing. Fusion based image enhancement techniques are fast and give great results. Fusion can of various types, out of which, multi-scale fusion proves to be the best choice. Burt and Kolczynski [7] proposed multi-scale fusion which involves combining of multiple derivative images in order to capture the specific significant properties from each derivative, such that the final image contains all the desired properties. Mertens et al. [8] proposed a method multi-scale fusion based approach to generate HDR images from multiple LDR images which were weighted according to their contrast, saturation and exposedness values to obtain the required features in the final image.

Fu et al. [9] proposed an image enhancement method for weakly illuminated images using multi-scale fusion. The approach was based on Retinex theory of light and involved illumination estimation and enhancement using multiple illumination derivatives which were finally fused to obtain the final enhanced image. Liu et al. [10] proposed an image enhancement method which utilized multiple differently exposed images prepared by tone mapping in grayscale. The approach fused these images by applying multi-scale fusion with the help of weight maps which were constructed by using parameter controlled contrast, saturation and exposedness values.

Various researchers have attempted low light image enhancement using different methodologies. Guo et al. [11] proposed an optimization-based strategy (LIME) for illumination map estimation and further, image enhancement. In LIME, the pixel-wise maximum of an image is taken as an estimate of illumination of the image. This illumination is 2 enhanced using an optimization-based approach. Fu et al. [12] attempted the simultaneous estimation of illumination and reflectance as part of Retinex theory, using a probabilistic prior. Further, Fu et al. [13] proposed a weighted strategy for estimation of illumination and reflectance. Some illumination estimation-based approaches are discussed in detail in [14]. Ghosh and Chaudhury [15] attempted the optimization of bilateral filtering for improved enhancement.

In this paper, we present a novel approach of image enhancement using multi-scale fusion. The content of the remaining paper is organized as follows. Section II explains the novel methodology proposed. Section III presents the results and constructive analysis of the proposed approach. Section IV concludes the paper.

## 2 Methodology

### 2.1. Motivation

Low-light images are difficult to interpret accurately. Images with underexposed or overexposed areas hide details, and thus objects contained in them are not easily comprehensible. Lowlight images with underexposed regions require enhancement of contrast and brightness so as to increase interpretability, without causing over-enhancement. Images containing overexposed areas need to reduce the exposure in such regions and enhance their contrast, to bring out the details hidden in them. These requirements call for bringing uniformity in illumination of the image, and not just a direct enhancement of brightness. In addition, the enhancement of contrast is also required, but without disturbing the natural feel of the image. Liu et al. [10] proposed an algorithm for enhancement of images using multi-exposure sequence generation. The algorithm first reduces the three-channel image to a single channel intensity image. The intensity image is used for generation of a multi-exposure sequence using an LDR tone mapping operator. Weight maps are then calculated for the images in the sequence using measures of contrast, exposedness and saturation, dependent on some parameters obtained as a result of minimizing an energy function. Further, the sequence is fused using multi-scale fusion. The success of the technique in enhancement of details and illumination of the image suggests the effectiveness of using multi-exposure sequence for fusion for image enhancement, and the weighting measures used. However, the minimization of energy function used in the algorithm is a time taking module and leads to an increase in the time complexity. The proposed method thus generates a multi-exposure sequence for generating candidates for fusion, but is computationally very efficient as it does not involve the optimization of an energy function. It has also been observed that the exposure sequence generated needs a derivative having an enhanced contrast because the images in the sequence are derived from the original image only, and hence may not have satisfactory contrast enhancement in either of them. This is not true of brightness as the sequence is generated by the manipulation of the intensities only. Hence, no separate instance with brightness enhancement is needed in the sequence.

Multi-scale fusion introduced in [7] involves the smooth amalgamation of images with the incorporation of required features. Naive fusion can also be used to blend images, but it has been observed that naive fusion often results in artifacts. This is because of the gradient involved in between pixel values. Multi-scale fusion, on the contrary, fuses the images without any artifacts because of the repeated downscaling and upscaling. Therefore, the proposed algorithm uses multi-scale fusion for blending input derivatives into the fused product.

### 2.2. Proposed Algorithm

The proposed algorithm enhances an image using multi-scale fusion of different input derivatives. The enhancement is performed in a series of four steps. Firstly, the image is converted into its HSV model, and the V channel of HSV model is used to generate a multi-exposure sequence of four images. Further, the contrast enhancement algorithm FCCE [16] is applied to the V channel and taken as the fifth input derivative with the multi-exposure sequence of four images being the first four input derivatives. Then, a weighting strategy is used to give higher weights to pixels having desired values of brightness and contrast. Finally, the input derivatives are fused using the weight maps generated in the previous step, using multi-scale fusion. This sequence of steps is discussed below. The framework of the algorithm is shown in Fig. 1.

**2.2.1. Multi-exposure Sequence Generation:** To perform IE, the algorithm takes the V channel of the HSV format of the image and performs enhancement on it before stacking the V channel back with the H and S channels which are kept unchanged. The V channel is used for enhancement because the V channel stores the intensity of the color specified by the other two channels of the image, and hence can be taken as the illumination. Next, a multi-exposure sequence is generated with respect to the V channel. The multi-exposure sequence, in essence, creates a number of different versions of the V channel with different exposures. Liu et al. generated a multi-scale exposure sequence in [10] with respect to the intensity map of the image, using a Low Dynamic Range (LDR) tone mapping operator. The proposed algorithm uses this operator to generate a multi-exposure sequence for the V channel. The LDR tone mapping operator is given by:

$$f(\mathbf{V}_{norm}, \lambda) = \mathbf{V}_{norm} + \frac{\mathbf{V}_{norm}}{\sqrt{\mathbf{V}_{norm}^2 + \lambda^2}}(\mathbf{V}_{max} - \mathbf{V}_{norm}) \tag{1}$$

where $i \in [1,4]$, $\mathbf{V}_{norm}$ denotes the normalized V channel of the image, $\mathbf{V}_{max}$ refers to the maximum value of the V channel, and $\lambda$ is a parameter controlling the jump in exposure from one image to the other in the sequence. The value of $n$ is taken to be 4 in the implementation, i.e., 4 images will be generated in the multi-exposure sequence, named $\mathbf{V}_1$ to $\mathbf{V}_4$.

**2.2.2. Generation of Contrast Enhanced Derivative:** It is an important requirement of vision-based systems that input images have well-defined edges and textural details. For the enhancement of details, it is required that contrast of the original low light image is enhanced.

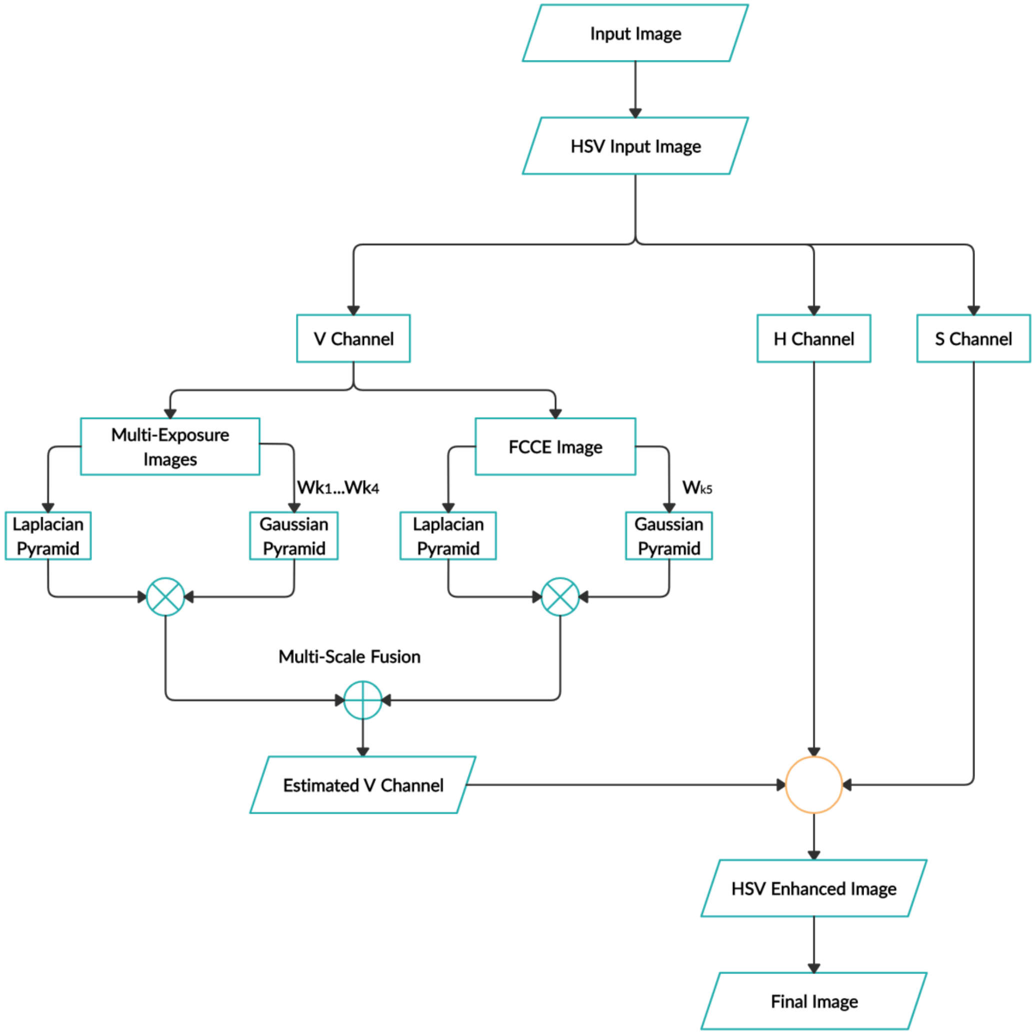


**Fig. 1:** Framework of the Proposed Algorithm

To account for the enhancement of contrast, a contrast-enhanced derivative of V channel of HSV model of the image is computed. The algorithm used for computing contrast-enhanced derivative is Fuzzy Contextual Contrast Enhancement (FCCE) [16]. The result of FCCE is then appended to the multi-exposure sequence generated in the previous step. Hence, the FCCE result is known as $\mathbf{V}_5$.

**2.2.3. Computation of Weight Maps:** The generated sequence of input derivatives is blended together to form a single image that gives us the refined V channel of the image. The blending of images is done using multi-scale fusion proposed in [7]. For multi-scale fusion, it is required that suitable weight maps for input derivatives be constructed. The weight maps should be constructed in a manner so as to include desired features in the fused image. Brightness and contrast are two features of image quality that are required to be at desired levels.

As far as brightness is concerned, it is observed that both overexposed and underexposed pixel values are not desired. Hence, it is required that we give higher weightage to pixels with values close to the middle value of 0.5, i.e. pixels of medium exposure, while lower weightage to pixels away from 0.5. To quantify this concept, the proposed methodology computes a brightness weight map for each image in the input derivative sequence. The computation of brightness weight map involves the use of a Gaussian kernel. It is given by:

$$\mathbf{Wb}_i = \exp\left\{-\frac{(\mathbf{V}_i - 0.5)^2}{2(0.25)^2}\right\} \tag{2}$$

where $\mathbf{Wb}_i$ is the brightness weight map, for $i \in [1,5]$, where $i$ denotes the input derivative index, and $\mathbf{V}_i$ denotes the input derivative pertaining to index $i$.

Further, it is required that for each pixel location, the corresponding pixel values in input derivatives having higher value of contrast be given more weightage than pixels with lower value of contrast. It has been observed that the first order differential of an image gives a good measure of the contrast. Pixel-wise gradient approximates the first order differential of the image. Hence, the proposed methodology uses the absolute value of the pixel-wise gradient as the contrast weight map. It is given as:

$$Wc_i(x,y) = \left|\sqrt{D_{x,i}^2 + D_{y,i}^2}\right| \tag{3}$$

$$\begin{aligned} D_{x,i} &= V_i(x,y) - V_i(x+1,y) \\ D_{y,i} &= V_i(x,y) - V_i(x,y+1) \end{aligned} \tag{4}$$

where $Wc_i(x,y)$ is the contrast weight map, for $i \in [1,5]$, where $i$ denotes the input derivative index, and $\mathbf{V}_i$ denotes the input derivative pertaining to index $i$.

The weight maps are normalized so that the weight values for all the input derivatives sum up to 1 at each pixel location. After normalization, the final weight map for each image is obtained by taking the arithmetic mean of the brightness and contrast weight maps. This is given by:

$$\mathbf{Wk}_i = \frac{(\mathbf{Wb}_i + \mathbf{Wc}_i)}{2} \tag{5}$$

where $\mathbf{Wk}_i$ denotes the final weight map for input derivative pertaining to index $i$.

**2.2.4. Multi-scale Fusion:** Burt and Adelson in [17] introduced the idea of Gaussian and Laplacian pyramids. A Gaussian pyramid is constructed by repeated downscaling of an image using a low-pass filter. On the other hand, a Laplacian pyramid is constructed by subtracting the immediately lower layer from each layer upscaling the lower layer using a filter that acts in reverse with respect to the low-pass filter used earlier. Burt and Kolczynski took the idea further in [7] and used it for the smooth blending of different images into one. In [7], images are blended using weight maps. Laplacian pyramids are constructed for input derivatives, while Gaussian pyramids are constructed for their weight maps. These pyramids are then used for fusing the images in a layered fashion, given by:

$$\mathcal{L}\{\mathbf{V}_{final}\}^l = \sum_{k=1}^{n} \mathcal{G}\{\mathbf{Wk}_i\}_k^l \, \mathcal{L}\{\mathbf{V}_i\}_k^l \tag{6}$$

where L denotes Laplacian pyramid and G denotes Gaussian pyramid. The resultant pyramid is summed up to obtain the fused image, $\mathbf{V}_{final}$.

The fused image $\mathbf{V}_{final}$ is considered to be the refined version of the V channel of the input low light image. Therefore, after computing $\mathbf{V}_{final}$, it is stacked back with the original H and S channels of the image. The HSV image thus obtained is converted into the RGB format to obtain the final enhanced image.

## 3 Experimental Analysis

We performed exhaustive experimentation for analyzing the performance of proposed method. We used images from: ExDark database [18], Barkeley segmentation database [19], and Nasa database [20] for the experimental analysis. The analysis is performed with various methods: WIE [13], LIME [11], FWE [9], and SRIE [21]. We analyze the proposed method using quantitative and qualitative analysis.

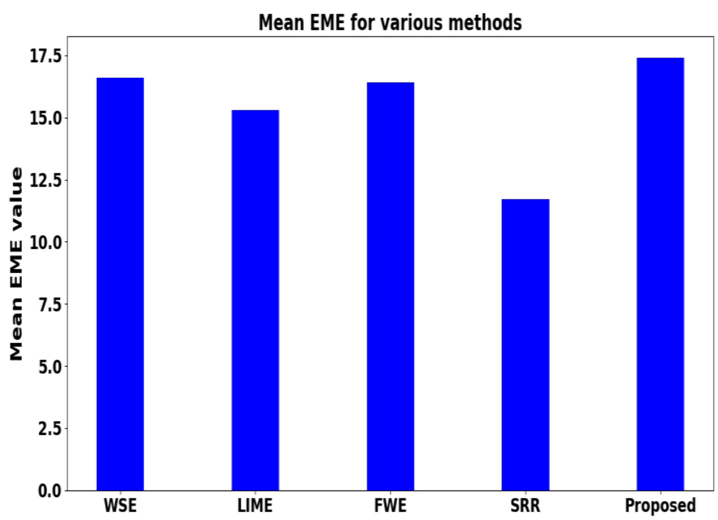


**Fig. 2:** Mean EME values for various enhancement methods.

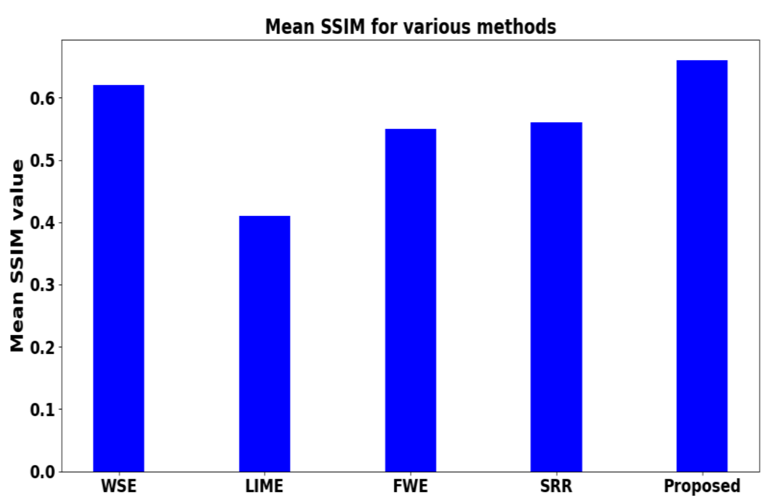


**Fig. 3:** Mean SSIM values for various enhancement methods.

### 3.1 Quantitative analysis

Qualitative analysis is required to analyse the quality of images. However, sometimes the qualitative analysis becomes subjective. To overcome this quantitative analysis is required. We analyze the proposed approach using EME, and SSIM [22].

EME is used to quantitatively analyze the output images for enhancement. EME is related to Weber's law and known as measure of enhancement. The higher the value of EME represents the superior enhancement. The analysis of mean EME values for various methods is shown in Fig. 2.

SSIM [22] shows the similarity of structural details. SSIM uses mean, standard deviation, and variance to compute similarity between image. The superior enhancement is represented by higher SSIM values. The analysis of various methods based on mean SSIM value is shown in Fig. 3.

### 3.2 Qualitative Analysis

Due to absence of universally accepted quantitative measure, it is required to perform qualitative analysis. Fig. 4-5 shows the qualitative analysis of the proposed method with other available method.

Fig. 4 shows 'Door', a low-light image and its enhanced versions with multiple methods. WIE provides good enhancement in regions with normal lighting but while dealing with the dark regions WIE fails to provide adequate enhancement. LIME provides better low-light enhancement. However, LIME fails to provide appropriate color constancy. Also, the results from LIME sometimes appear to be over-enhanced. FWE provides adequate low-light enhancement with appropriate color constancy. However, the contrast of the image is not proper. FWE sometimes fails to provide appropriate contrast. SRIE provides comparable enhancement. However, sometimes SRIE provides smoothing effect in the enhanced images with is not desirable n few cases. The proposed method performs appropriately for low-light enhancement and provides color constancy with proper contrast in the image. It can be noticed from Fig. 4 that proposed approach is providing superior result from majority of the methods.

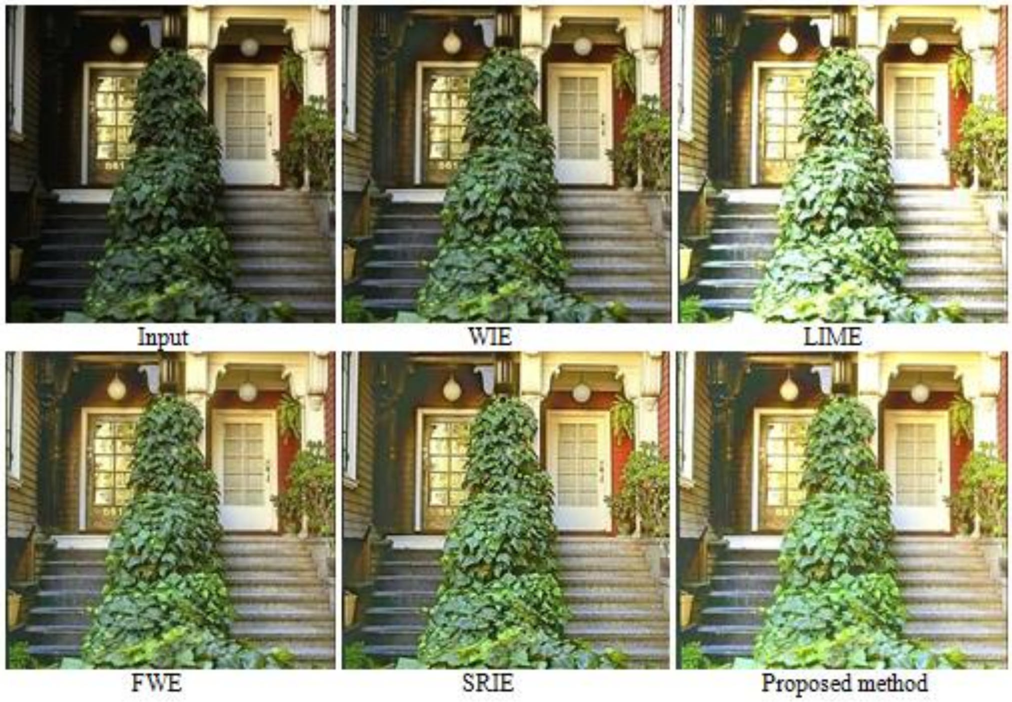


**Fig. 4**. 'Door' and results of several algorithms

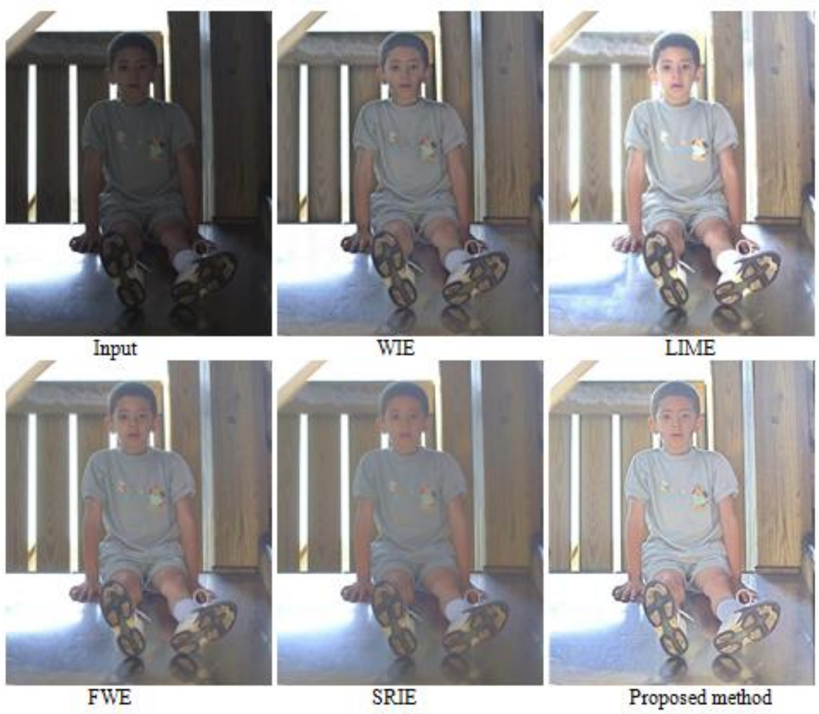


**Fig. 5.** 'Boy' and results of several algorithms.

The 'Boy' image with non-uniform lighting condition and its enhanced images is shown in Fig. 5. It can be notices that WIE fails to improve lightness in the darker regions. LIME provides over-enhancement in few regions of the images. LIME fails to provide color constancy. FWE provides limited enhancement in low-light regions. FWE fails to enhance darker regions. SRIE provides result with poor contrast and smoothing effect. It can be observed from the Fig. 5 that the proposed method improves the lightness in darker regions while having appropriate color constancy.

## 4 Conclusion

The paper provides a new approach for low-light image enhancement using image fusion. The proposed method achieves appropriate low-light image enhancement. Further, the method effectively deals with images with non-uniform lightning conditions. The superiority of proposed approach is validated by the experimental analysis over large set of images. The proposed method provides low-light image enhancement with almost no artifacts. Moreover, the proposed method provides appropriate color constancy with proper lightness.

## References

1. R. C. Gonzalez and R. E. Woods, Digital Image Processing (3rd Edition). USA: Prentice-Hall, Inc., **(2006)**.
2. M. Abdullah-Al-Wadud, M. H. Kabir, M. A. Akber Dewan, and O. Chae, “A dynamic histogram equalization for image contrast enhancement,” IEEE Transactions on Consumer Electronics, vol. 53, no. 2, **(2007)**, pp. 593– 600.
3. A. S. Parihar and O. P. Verma, “Contrast enhancement using entropy- based dynamic sub-histogram equalisation,” IET Image Processing, vol. 10, no. 11, **(2016)**, pp. 799–808.
4. L.Shen,Z.Yue,F.Feng,Q.Chen,S.Liu,andJ.Ma,“Msr-net:low-light image enhancement using deep convolutional network,” **(2017)**.
5. M. Gharbi, J. Chen, J. T. Barron, S. W. Hasinoff, and F. Durand, “Deep bilateral learning for real-time image enhancement,” ACM Trans. Graph., vol. 36, no. 4, **(2017)**.
6. K. G. Lore, A. Akintayo, and S. Sarkar, “Llnet: A deep autoencoder approach to natural low-light image enhancement,” Pattern Recognition, vol. 61, **(2017)**, pp. 650 – 662.
7. P. J. Burt and R. J. Kolczynski, “Enhanced image capture through fusion,” in Proceedings of the 1993 (4th) International Conference on Computer Vision. IEEE, **(1993)**.
8. T. Mertens, J. Kautz, and F. Van Reeth, “Exposure fusion: A simple and practical alternative to high dynamic range photography,” Computer Graphics Forum, vol. 28, **(2008)**, pp. 161 – 171.
9. X. Fu, D. Zeng, Y. Huang, Y. Liao, X. Ding, and J. Paisley, “A fusion-based enhancing method for weakly illuminated images,” Signal Processing, vol. 129, **(2016)**, pp. 82–96.
10. S. Liu and Y. Zhang, “Detail-preserving underexposed image enhance- ment via optimal weighted multi-exposure fusion,” IEEE Transactions on Consumer Electronics, vol. 65, **(2019)**, pp. 303–311 .
11. X. Guo, Y. Li, and H. Ling, “Lime: Low-light image enhancement via illumination map estimation,” IEEE Transactions on Image Processing, vol. 26, no. 2, **(2017)**, pp. 982–993 .
12. X. Fu, Y. Liao, D. Zeng, Y. Huang, X. Zhang, and X. Ding, “A proba- bilistic method for image enhancement with simultaneous illumination and reflectance estimation,” IEEE Transactions on Image Processing, vol. 24, no. 12, **(2015)**, pp. 4965–4977.
13. X. Fu, D. Zeng, Y. Huang, X. Zhang, and X. Ding, “A weighted varia- tional model for simultaneous reflectance and illumination estimation,” in 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), **(2016)** June.
14. K. Singh and A. S. Parihar, “A comparative analysis of illumination estimation based image enhancement techniques,” in 2020 International Conference on Emerging Trends in Information Technology and Engi- neering (ic-ETITE), **(2020)**.
15. S. Ghosh and K. N. Chaudhury, “Fast bright-pass bilateral filtering for low-light enhancement,” in 2019 IEEE International Conference on Image Processing (ICIP). IEEE, **(2019)**, pp. 205–209.
16. A. S. Parihar, O. P. Verma, and C. Khanna, “Fuzzy-contextual contrast enhancement,” IEEE Transactions on Image Processing, vol. 26, no. 4, **(2017)**, pp. 1810–1819.

17. P. Burt and E. Adelson, "The laplacian pyramid as a compact image code," IEEE Transactions on Communications, vol. 31, **(1983)**, pp. 532–540.
18. Y. P. Loh and C. S. Chan, "Getting to know low-light images with the exclusively dark dataset," Computer Vision and Image Understanding, vol. 178, **(2019)**, pp. 30 – 42.
19. D. Martin, C. Fowlkes, D. Tal, J. Malik et al., "A database of human segmented natural images and its application to evaluating segmentation algorithms and measuring ecological statistics." Iccv Vancouver, **(2001)**.
20. G. Woodell, "Retinex image processing," https://dragon.larc.nasa.gov/ retinex/pao/news/., accessed: **(2019)**.
21. M. Li, J. Liu, W. Yang, X. Sun, and Z. Guo, "Structure-revealing low- light image enhancement via robust retinex model," IEEE Transactions on Image Processing, vol. 27, no. 6, **(2018)**, pp. 2828–2841.
22. Z. Wang, A. C. Bovik, H. R. Sheikh, and E. P. Simoncelli, "Image quality assessment: from error visibility to structural similarity," IEEE transactions on image processing, vol. 13, no. 4, **(2004)**, pp. 600–612.