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Nighttime Image Enhancement: A Review of Topical Concepts

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Abstract

With the increasing spread of nighttime images and their importance in human lives, and the development of computer vision, producing images with the highest possible quality is paramount. Nighttime images have been improved over the past decades by introducing many methods, each of which uses different techniques to enhance the quality of such images that have many degradations, such as poor illumination, uneven lighting, low contrast, widespread noise, and unnatural colors. This paper reviews twelve modern-day algorithms that can be used to enhance nighttime images by presenting the concepts, work mechanisms, processing abilities, and performance evaluations for each algorithm. Likewise, these algorithms are evaluated using three metrics with their processing times, and the advantages and disadvantages of each algorithm are given. Such a review can help researchers understand which concepts to select for development, which drawbacks to avoid when developing an algorithm in this field, and what the currently available concepts are.

Keywords: Nighttime, Image Enhancement, Image Processing, Illumination, Evaluation.

1 Introduction

Digital images are visual illustrations of data in a numerical form, having small dots called pixels that contain information about brightness and color [22]. Such digital images can be acquired by digital cameras, scanned from physical photographs, or generated by computer software [23]. In recent years, capturing images at night has notably increased [24] as nightlife activities have grown tremendously, and the effect of social media has increased in recent years [25]. The images taken under poor lighting conditions, such as those taken at night or indoors, are of low light and contrast, contain noise, and have unnatural colors [1], as shown in Figure 1. Therefore, image-related information is hidden or lost, which limits the usefulness of real-world applications [2]. Many methods of image enhancement have been created or developed to improve different attributes of the image, including illumination [3].

Figure 1. Samples of images captured at night.

The field of nighttime image enhancement continues to evolve due to the importance of these images in essential applications such as surveillance forensics, night vision equipment, facial recognition, and bug detection [4]. Therefore, techniques for improving images captured at nighttime must not be limited to enhancing lighting only but must also consider suppressing hidden noise in dark areas [5], preserving bright areas from increasing their brightness [6], and avoiding excessive enhancement, in addition to improving contrast and making colors more natural, and make sure not to generate any distortions. Many studies on improving nighttime images have been developed, where each study uses a different processing technique, including the Retinex, fusion, camera response, gray level transformation, histogram, artificial intelligence and many more [7]. Some methods are applied to the RGB color model, and others to the HSI or HSV color models, in addition to the utilization of

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logarithmic image processing and statistical and exponential approaches. This paper aims to provide a comprehensive review of twelve proposed algorithms related to nighttime image enhancement. Figures 2 to 13 demonstrate the results of each of the reviewed algorithms.

In 2013 [8], Wang et al. proposed a naturalness preserved enhancement (NPE) algorithm. It aims to enhance non-uniform illumination photographs while maintaining their natural appearance. This algorithm starts by implementing the bright-pass filter to attain the illumination and the reflectance and ensuring that the reflectance values are constrained within the range of zero to one. Then, the bi-log transformation approach is applied to filter the illumination information, ensuring that the details are not overwhelmed by spatial variations while maintaining the order of lightness. The output image is ultimately obtained by synthesizing the reflectance and the mapped illumination.

Figure 2. Some results of the NPE algorithm.

In 2016 [9], Fu et al. introduced a fusion-based enhancement (FBE) algorithm that utilizes a morphological closing-based technique to estimate illumination. This algorithm begins by decomposing the image into two components: reflectance and illumination. Next, the illumination part is enhanced using a specialized contrast enhancement method of adaptive histogram equalization. Also, a sigmoid function is applied for further enhancement. The output image is generated by applying a multiscale and weighted fusion process.

Figure 3. Some results of the FBE algorithm.

In 2016 [10], Guo et al. proposed an efficient low-light image enhancement (LIME) algorithm. It initially determines the brightness of each pixel separately by selecting the highest value from the R, G, and B channels. Next, the generated illumination map is enhanced by applying a structural constraint, resulting in the final illumination map. Finally, the revealed noise is reduced by converting from the RGB to YCbCr and implementing the BM3D denoising model on the Y channel.

Figure 4. Some results of the LIME algorithm.

In 2017 [11], Ying et al. introduced a bio-inspired multi-exposure fusion (BIMEF) algorithm. Initially, a weight matrix is used for image fusion by employing an illumination estimation process. Next, the developed camera response model is utilized to generate multi-exposure images. Afterwards, the optimal exposure ratio is determined to ensure the image is exposed adequately in the under-exposed areas. The algorithm's output is obtained by combining the filter image with the input image based on a weight matrix.

Figure 5. Some results of the BIMEF algorithm.

In 2018 [12], Li et al. introduced the robust retinex model (RRM), which aims to enhance the performance of low-light images with high noise levels. The noise map is estimated to be attenuated when improving the illumination using the retinex model as the central concept. It can be attained concurrently by estimating a reflectance map that reveals the structure, as well as an illumination map that is smoothed in a piecewise manner. Furthermore, a novel augmented Lagrange multiplier-based

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alternating direction minimization algorithm, which does not involve logarithmic transformation, is presented to solve optimization problems for noise attenuation in the reflectance component.

Figure 6. Some results of the RRM algorithm.

In 2018 [13], Ren et al. proposed a sequential decomposition (SD) algorithm. The main objective here is to improve the illumination in the dark areas while attenuating the hidden noise. It starts by applying a sequential approach, which includes a retinex decomposition. This approach estimates the piecewise smoothed illumination and the noise-suppressed reflectance sequentially. Then, the lighting layer is fine-tuned once the illumination and reflectance components by imposing spatial smoothness on each element. Afterwards, the smooth illumination map is isolated. At the same time, most of the noise remains in the reflectance part, and weighted matrices are utilized to mitigate noise while enhancing the reflectance and contrast and generating the output image.

Figure 7. Some results of the SD algorithm.

In 2018 [17], Ren et al. proposed a camera response (CR) framework that utilizes the response characteristics of cameras. This approach integrates the conventional retinex model with the CR models. Initially, it determines an appropriate camera response model and its corresponding parameters. Subsequently, illumination estimation techniques are used to calculate the exposure ratio for every pixel. The chosen camera response model is employed to modify each pixel to achieve the intended exposure based on the estimated exposure ratio map and yield the output.

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Figure 8. Some results of the CR algorithm.

In 2019 [14], Dai et al. proposed a fractional-order fusion (FOF) algorithm. Firstly, fractional order is utilized to extract illumination from the input image. Furthermore, the appropriate illumination adjustment approach is implemented to adjust the luminosity. Afterwards, the BM3D technique is employed to reduce the noise that arises from the low-light regions. Next, a fusion approach is utilized to generate the output by counterbalancing the loss of intricate information caused by filtering while simultaneously enhancing image brightness and preventing excessive enhancement.

Figure 9. Some results of the FOF algorithm.

In 2019 [15], Al-Ameen proposed an illumination boost (IB) algorithm. It utilizes two specialized logarithmic and exponential functions to boost the mid and low intensities while preserving high intensities. Next, the resulting outputs from these two functions are merged utilizing a modified logarithmic image processing technique to acquire an image that encompasses the distinctive features of both images. After that, an altered S-curve function is employed to enhance the overall luminosity of the image. Lastly, a linear scaling function is used for intensity redistribution to create the output.

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Figure 10. Some results of the IB algorithm.

In 2019 [16], Wang et al. proposed an adaptive image enhancement (AIE) method that utilizes the color-space transformation algorithm and the multiscale decomposition technique. The initial RGB image is transformed into the HSV color space, and the V component is considered. Afterwards, the parameters of the adaptive enhancement functions are modified based on the estimated illumination distribution, generating two images. Next, image fusion is employed to extract the salient data from the image to amplify the V component. Lastly, the image is transformed from the HSV to RGB color space to provide the algorithm's output.

Figure 11. Some results of the AIE algorithm.

In 2020 [18], Hao et al. introduced a semi-decoupled decomposition (SDD) method based on the retinex theory. This method efficiently decomposes a given image using a semi-decoupled approach. The illumination layer I is estimated gradually using only the input image S, which is also filtered by a total variation model. In contrast, the reflectance layer R is calculated simultaneously using both S and the intermediate layer I. Furthermore, the estimation of R suppresses the generated noise. The output is generated by composing the filtered components.

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Figure 12. Some results of the SDD algorithm.

In 2020 [19], Al-Hashim and Al-Ameen introduced a retinex-based multiphase (RBMP) algorithm was introduced that effectively and quickly improved the quality of low-light images. The RBMP calculates the illumination image. Next, the logarithms of both the illumination and original images are calculated and then subtracted using a modified LIP method. Subsequently, the result is subjected to a gamma-corrected sigmoid function and further improved through a normalization method.

Figure 13. Some results of the RBMP algorithm.

In addition to visually comparing these algorithms, the resulting images are evaluated using three quality metrics in addition to the computed processing speed for each method. Moreover, the advantages and disadvantages of each algorithm are given for more beneficial reference. The structure of this paper is as follows: Section 2 describes the metrics used for image quality evaluation; Section 3 demonstrates the comparisons and states the related discussions; Section 4 gives a brief conclusion.

2 Methodology

Image quality assessment (IQA) determines the degree of precision in images [26]. Image quality can be evaluated through two approaches: subjective and objective [27]. Subjective evaluation approaches rely on the subjective evaluation of a human viewer on the characteristics of an image. They are expensive, necessitate many people, and cannot be automated in real-time. Subjective IQA approaches often utilize mean opinion scores, in which various viewers provide ratings based on their

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views of photo quality, and these opinions are translated into numerical values. Objective evaluation utilizes computational models that can forecast perceived image quality [28]. There are three primary categories of objective methods [7]:

1. Full-reference (FR) methods [29]: Evaluate the quality by comparing the image to a reference one that is considered perfect, such as comparing the original image to a noisy or restored version of the same image.
2. Reduced reference (RR) methods [30]: Evaluate the quality of a degraded and filtered image by comparing certain features from both images.
3. No-reference (NR) methods [31]: Evaluate the quality of a single image without any comparison to a reference image.

This paper used three objective IQA metrics, two NR metrics, BRISQUE and CFN, and one RR metric, LOE. The blind reference-less image spatial quality evaluator (BRISQUE) utilizes natural scene statistics for constructing a distortion metric. If the unknown image is severely distorted, it is unlikely that the statistical regularity of that image would correspond to that of a typical natural image. Lower BRISQUE values correspond to less distortion, indicating better quality, whereas higher values imply significant distortion and poorer quality [20]. The colorfulness (CFN) metric is a numerical measure that quantifies the intensity of colors based on the standard deviation and the mean values of the image. The result of this metric is a numerical number, with the highest value indicating better color quality [21]. The lightness order error (LOE) calculates the illumination error between the input and recovered images. The numerical value is the output of this metric, in that a lower score represents good natural illumination [19]. To sum up, the BRISQUE measures the naturalness, the CFN measures the color quality, and the LOE estimates the illumination quality.

3 Results and Discussion

This section presents the results and discussions for the conducted review. Table 1 shows the numerical readings with the advantages and disadvantages of the reviewed methods. Figure 14 and Figure 15 illustrate the average scores in Table 1. As for the reviewed algorithms, The NPE algorithm recorded the second slowest algorithm in terms of execution time. As for the LOE and BRISQUE values, they ranked in the middle. The CFN results were appropriate because their colors were adequate. Moreover, The FBE algorithm recorded the second worst average reading in the LOE, while proper readings were obtained in BRISQUE; the processing speed was reasonable, and the CFN scale recorded acceptable results.

Table 1. Comparisons between algorithms

Method	Figure	LOE	BRISQUE	CFN	Time(sec.)	Advantages	Disadvantages
NPE	Fig.2	446.5148	15.5915	62.7849	30.601696	Pleasing illumination and colors	Slow, Introduce halo effects
	Fig.3	417.8524	54.0239	26.6315	30.645468		
	Fig.4	326.8999	38.6489	39.7785	39.578862		
	Avg.	**397.0890**	**36.0881**	**43.0649**	**33.608675**		
FBE	Fig.2	690.0032	8.8309	52.2521	0.891102	Clear colors	Low brightness
	Fig.3	334.0480	56.3467	20.4819	0.657330		
	Fig.4	409.2049	30.3807	42.9535	0.918185		
	Avg.	**477.7520**	**31.8527**	**38.5625**	**0.822205**		
LIME	Fig.2	796.4971	25.2895	80.5991	2.214376	Attractive to the eye	Over-enhancement
	Fig.3	518.2967	53.7174	32.2449	1.774110		
	Fig.4	627.5631	37.9648	51.6453	2.221356		
	Avg.	**647.4523**	**38.9905**	**54.8297**	**2.069947**		
BIMEF	Fig.2	195.8635	7.2609	50.4632	0.363399	Fast, improved contrast	Provide over-exposure
	Fig.3	124.4485	46.6936	16.0920	0.722941		
	Fig.4	93.4066	42.6328	25.5233	0.726351		
	Avg.	**137.9062**	**32.1957**	**30.6928**	**0.121566**		
RRM	Fig.2	361.4795	24.2354	67.7982	70.571056	Decent illumination enhancement	Very slow
	Fig.3	184.0802	59.5685	19.5568	56.104993		
	Fig.4	167.1171	38.3533	39.1519	116.924326		
	Avg.	**237.5589**	**40.7190**	**42.1689**	**81.200125**		
SD	Fig.2	369.7463	27.5851	67.2083	13.940415	Reduce the noise	Deliver distortions
	Fig.3	193.2483	55.1049	18.5611	19.184834		
	Fig.4	171.5607	43.2473	38.6279	13.977965		
	Avg.	**244.8517**	**41.9791**	**41.4657**	**15.701071**		
FOF	Fig.2	291.2524	11.0877	52.7897	27.398343	retain naturalness	Slow and generate noise

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	Fig.3	294.7564	48.5266	20.4273	28.780623		
	Fig.4	232.8708	43.9548	34.1529	19.582278		
	Avg.	**272.9598**	**34.5230**	**35.7899**	**25.253748**		
IB	Fig.2	1.7424	8.3960	58.6565	0.075529	Fast, with high illumination enhancement	Not fully automatic
	Fig.3	0.2258	46.2252	16.3710	0.085920		
	Fig.4	0.0971	32.1951	29.9657	0.093899		
	Avg.	**0.6884**	**28.9387**	**34.9977**	**0.085116**		
AIE	Fig.2	5.2437	10.6069	59.8662	0.202612	Balanced colors with adequate illumination	Insufficient contrast and noise amplification
	Fig.3	22.0205	65.5681	33.1483	0.160694		
	Fig.4	12.6694	47.4091	51.1338	0.205631		
	Avg.	**13.3112**	**41.1947**	**48.0494**	**0.189645**		
CR	Fig.2	399.7342	9.0336	64.5556	1.337729	Fewer illumination distortions	White shadows around the boundaries with unnatural color
	Fig.3	59.3315	49.5568	20.7979	0.729904		
	Fig.4	11.7495	34.8996	34.2014	0.689093		
	Avg.	**156.9384**	**31.1633**	**39.8516**	**0.918908**		
SDD	Fig.2	361.8106	23.2171	61.1725	29.715303	Acceptable illumination	Slow, Generate artifacts
	Fig.3	300.1516	55.0082	22.2377	31.749675		
	Fig.4	289.5769	42.3045	33.5965	38.740263		
	Avg.	**317.1797**	**40.1766**	**39.0022**	**33.401747**		
RBMP	Fig.2	11.8878	5.0378	45.0668	0.952800	Fast with proper illumination enhancement	It needs more color enhancement
	Fig.3	12.3102	47.1185	15.7131	0.310975		
	Fig.4	15.7961	44.5095	26.5307	0.396607		
	Avg.	**13.3313**	**32.2219**	**29.1035**	**0.553460**		

The LIME algorithm is the best in terms of color quality. It recorded the highest value on the CFN metric, meaning the best compared to the considered algorithms. Thus, the worst values in the LOE metric were recorded, providing the worst illumination compared to the other algorithms. As for the BRISQUE metric, it recorded inappropriate values, yet the average processing time was rather good. The BIMEF algorithm had appropriate values in the LOE and BRISQUE metrics. Still, its colors were unnatural, so it recorded the second worst value in CFN yet was the second fastest algorithm.

Likewise, the RRM algorithm provided the slowest performance, yet its readings were reasonably good according to LOE, in addition to delivering appropriate colors. Thus, values on the CFN metric were reasonable but not adequate on the BRISQUE metric. The SD algorithm is considered the worst in naturalness according to BRISQUE, meaning its results have little distortion and are not of decent visible quality. It was suitable in the LOE and CFN scales, while the processing speed was acceptable. The FOF algorithm provided neutral results on the LOE and BRISQUE metrics and was not color-satisfactory according to the CFN metric. The processing speed was somewhat slow. The IB algorithm recorded the best in terms of illumination, that is, the best in LOE and BRISQUE, and it also recorded the fastest average runtime. Still, the colors are insufficient, so it recorded low results on the CFN metric.

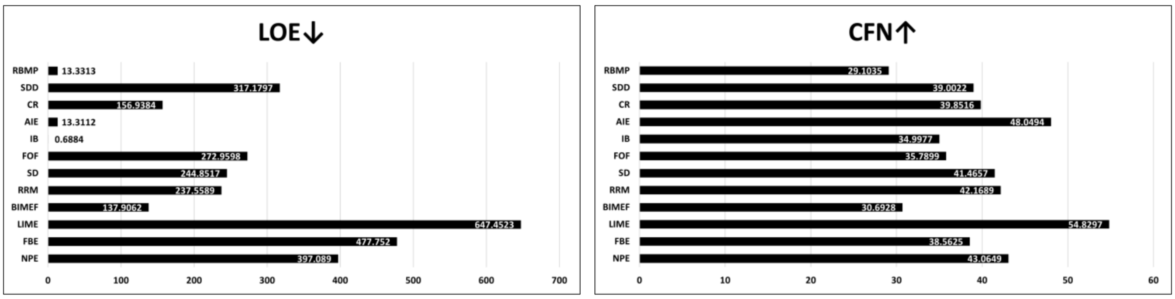

Figure 14. The average LOE and CFN scores.

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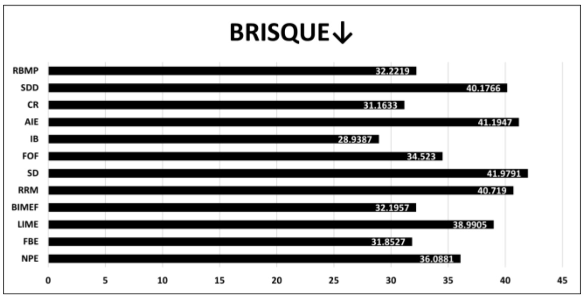

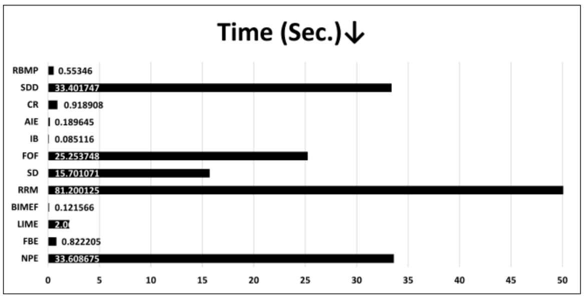

Figure 15. The average BRISQUE and runtime readings.

The AIE algorithm recorded the second-best result in LOE and CFN and ranked the second-worst in BRISQUE. The execution speed is mediocre. The CR algorithm provided acceptable results, as stated by LOE and BRISQUE, and it recorded reasonably in CFN as well. The processing speed was appropriate. The SDD algorithm recorded unacceptable results in the LOE and BRISQUE because the illumination was insufficient while averaging in terms of CFN, and it is considered slow in terms of processing speed. Finally, the RBMP algorithm was the worst in terms of the CFN metric because the colors of the images were dull and unnatural, but in terms of the LOE and BRISQUE scales, it was satisfactory, and the processing speed was low. Given all these statements and analysis, a researcher can select an algorithm and develop it considering its drawbacks to become better for nighttime image enhancement.

4 Conclusion

Different research works have been conducted by numerous researchers on the topic of nighttime image enhancement. Nighttime images are subject to many distortions, including illumination flaws, poor contrast, color distortions, and undesirable noise. These degradations may impact the quality of images, and, as a result, they need to be appropriately processed to achieve satisfying results in terms of perceived quality and presented details. The enhancement algorithms that have been proposed in recent years have shown insufficient efficiency in filtering nighttime images due to their lack of ability to address all the issues described above, high complexity, introduce distortions, and cause color inaccuracies. Hence, there is still a demand for the development of high-quality algorithms, thus leaving room for further progress in this research field.

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