

Retinex-Based Algorithm to Enhance Underlit Archaeology Images Taken in Semi-or-Fully Enclosed Environments

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ABSTRACT

Archaeology is strongly related to digital images, as they visually represent scenes and objects. Archaeological images are rarely obtained in perfect quality, as degradations often affect them. One constant degradation is uneven illumination. It leads to dim, underlit results with unpleasant appearances. This paper provides a fast Retinex-based algorithm to better brighten underlit archaeological images. The Retinex model is adapted using statistical and image processing methods. This aids in providing brighter and more perceptually pleasing results. The main modifications to the Retinex algorithm include the following: (i) utilize a new approach to compute the reflectance component; (ii) add a statistical method to further improve the reflectance; (iii) apply a linear stretching procedure to guarantee full dynamic range pixel distribution. These modifications help to get more uniform illumination in the results. The algorithm efficiently enhanced brightness and tonality, revealing fine textures and intricate details. The resulting images demonstrate significant balance in illumination compared to the original counterparts. Likewise, comparisons are made with six algorithms having dissimilar concepts, and evaluations are made using two assessment methods. The results are promising as the proposed algorithm performed well visually and objectively, scoring an average LOE of 195.14 and average runtime of 0.798 seconds. This indicates a successful tackling of a distinctive challenge, offering a non-complex solution.

Keywords: Underlit, Archaeological Images, Low-Light, Retinex, Indoor, Image Enhancement

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1. OVERVIEW

Archaeological images represent visual interpretations. They are used to document and preserve historical heritage. These images captured the information of ancient artifacts, ruins, sculptures, and excavations [1]. In this context, capturing images in varying environments, light conditions, and imaging technologies can result in dim, underlit images. In addition, images captured indoors can appear dark and have poor lighting [2]. The loss of details and information in such images makes the interpretation and analysis of information challenging [3]. Hence, image enhancement (IE) techniques are applied to solve this issue and improve overall clarity. Furthermore, this can boost the illumination to make most of the hidden and lost information more visible. IE techniques can be employed to enhance the brightness to improve the quality [4]. Accordingly, low illumination refers to low brightness and dim light, leading to detail loss [5]. In archaeological images, the underlit effect is common, occurring when the light from beneath the subject creates shadows, obscuring features, making them appear with vanished details [6]. Hence, many IE algorithms that utilize different processing notions have been introduced.

One interesting algorithm is the single-scale Retinex (SSR). It is widely used to improve brightness for various real-life applications [7]. The classical SSR algorithm can enhance brightness, but the resulting images remain generally poorly lit and may be affected by other degradations. Other algorithms have also been introduced and utilized by renowned researchers. Fu et al. [16] proposed a variational framework that employs a bright channel prior (BCP) concept. The BCP approximates illumination by using statistical priors on brightness distribution to enhance the details. Tanaka et al. [17] introduced a gradient-based (GB) approach. GB improves details by intensifying gradient magnitudes while suppressing noise to preserve natural structures. Singh and Bhandari [18] employed principal component analysis (PCA) via a reflection model. PCA separates illumination and reflectance information distinctly to improve brightness, contrast, and color fidelity. Demir and Kaplan [19] developed a sharpening-smoothing filtering (SSF) approach. SSF balances detail enhancement and noise suppression to uphold structural truthfulness. More recently, Sundari and Keerthi [20] utilized Sakaguchi-type functions (STF). STF aimed to attain nonlinear enhancement with adaptive brightness modification.

Despite these advances and developments, existing algorithms often face trade-offs between different aspects. Such aspects include artifact generation, color distortion, equalization efficiency, and computational complexity. Thus, developing pioneering algorithms is vital to reach well-corrected illumination. Accordingly, the SSR is decidedly relevant for archaeological images because it successfully separates illumination and the reflectance information. This trait enables improved processing for intrinsically obscured details. Additionally, the SSR, which emulates the human visual perception, was designed to enhance visibility while preserving structural originality. Furthermore, they have low to manageable computational complexity, making them practical for large images without needing extreme resources. Hence, the classical SSR is improved to deliver adequate illumination for underlit archaeological images. In this context, tests with different images were conducted, and the results were promising. This study is arranged in this way: the next section details the developed algorithm and its mechanism. Section 3 describes the dataset and the results of the developed algorithm. Lastly, the conclusion is presented in Section 4.

2. PROPOSED ALGORITHM

The Retinex theory (short for Retina + Cortex) was originally introduced by Edwin Land in the 1960s [8]. It is used in image enhancement, specifically for illumination and contrast correction. This model was created to be more visually aligned with human vision using the Retina and Cortex terms, intended for image perception. The human eye can see an object without the effect of light variations. For example, humans can identify that white paper is white, whether in the shadow or the sun. This happens because the brain processes relative reflectance rather than absolute brightness [9]. Many algorithms have been introduced using this concept, and one worth considering is the SSR. This model deems an image to have two principal elements: reflectance and illumination. The collective impact of these two components forms the perceived image. Simply put, when the light illuminates an object, its reflection is generated, making the object seen [10]. The SSR works as follows [11]: the input image is expressed in terms of hue, saturation, and value (HSV), working only on the value channel. The illumination part $L_{(i,j)}$ of the V component $W_{(i,j)}$ is estimated in the following manner:

$$L_{(i,j)} = W_{(i,j)} * G_{(i,j)} \quad (1)$$

where $(*)$ denotes the frequency domain convolution and $G_{(i,j)}$ denotes a Gaussian filter generated as:

$$G_{(i,j)} = \frac{1}{\sum_{i=1}^R \sum_{j=1}^C \exp\left(-\frac{(P^2 + Q^2)}{2\sigma^2}\right)} \cdot \exp\left(-\frac{(P^2 + Q^2)}{2\sigma^2}\right) \quad (2)$$

where $(\cdot)$ denotes multiplication, i and j denote image coordinates, R and C denote the dimensions, P and Q denote horizontal and vertical gray gradients, and (σ) is a scalar that controls the brightness scale. The Gaussian filter reduces the high-frequency components of $W_{(i,j)}$, assuming the illumination variations happen at a much lower frequency. Once the illumination part is obtained, the reflectance (enhanced image) $E_{(i,j)}$ is estimated as:

$$E_{(i,j)} = \log(W_{(i,j)}) - \log(L_{(i,j)}) \quad (3)$$

The algorithm has a simple structure and few computations. It works well in some situations but may not adapt to dissimilar lighting levels. Hence, it has been a focus point for researchers in the past decades for its simplicity, closeness to the human visual system, and definite development potential. Thus, the classical SSR is further developed to process the low-light archaeology images captured in semi- or fully enclosed environments. First, two components are prepared in the following manner:

$$U_{(i,j)} = \log(W_{(i,j)} + \varepsilon) \quad (4)$$

$$V_{(i,j)} = \log(L_{(i,j)} + \varepsilon) \quad (5)$$

where $\varepsilon = 0.01$, a minor value used to evade having $\log(0) = \infty$. Next, instead of using the direct subtraction in Eq. (3) to compute the reflectance, a modified subtraction model of logarithmic image processing (LIP) is utilized for better reflectance generation. LIP has more consistency since it follows more physically meaningful image formation rules, which the classical SSR does not follow. The classical SSR assumes an optimal logarithmic response, which may not be held for real-life images. Different LIP subtraction models exist, but one noteworthy model is the one given in [12], which can be written as:

$$A_{(i,j)} = \frac{(U_{(i,j)} - V_{(i,j)})}{1 - (U_{(i,j)} \cdot V_{(i,j)})} \quad (6)$$

However, the multiplication makes the denominator negative or with a small value, causing incorrect intensity scaling or division by near-zero values, leading to unwanted distortions. To overcome this issue, the multiplication is replaced with the addition in the demonstrator, and the new LIP model is written as:

$$T_{(i,j)} = \frac{(U_{(i,j)} - V_{(i,j)})}{1 - (U_{(i,j)} + V_{(i,j)})} \quad (7)$$

This improved version always has a positive denominator: the division by negative or small values is avoided, leading to better intensity scaling and preventing unwanted distortions. Moreover, it better follows the LIP theory because intensity interactions are better modeled using addition instead of multiplication. Next, the improved reflectance $T_{(i,j)}$ is further refined using a curvy transformation using

the CDF of the generalized logistic distribution Type II (CDF-GLD-II), expressed in the following formula [13]:

$$F_{(i,j)} = 1 - \frac{\exp(-\eta \cdot T_{(i,j)})}{(1 + \exp(-T_{(i,j)}))^\eta} \quad (8)$$

where η represents an enhancement factor, satisfying ($\eta > 1$), in that increasing η leads to higher illumination. The CDF-GLD-II is an S-shaped model that acts like a nonlinear intensity transformer. When the reflectance is estimated, it often suffers from somewhat compressed dynamic range. This is due to the utilization of logarithmic transformations. The GLD-II CDF can deliver a flexible, S-shaped, nonlinear mapping. Likewise, it can adaptively redistribute the values in a controlled way. This expands low values as well as compresses high values while delivering smooth mid-tones. By applying the GLD-II CDF, the reflectance becomes more perceptually balanced. This function yields improved detail visibility and tonal separation, making it a powerful refinement phase. Still, the intensity values of $F_{(i,j)}$ do not cover the full possible intensity range, leading to incorrect tonality. Hence, the linear stretching (LS) method in [14] is used to guarantee that the full range is utilized. This stabilizes variations, leading to a more uniformly corrected image. The LS method can be mathematically expressed as:

$$\alpha = \frac{1}{\max(F_{(i,j)}) - \min(F_{(i,j)})} \quad (9)$$

$$\beta = \frac{\min(F_{(i,j)})}{\max(F_{(i,j)}) - \min(F_{(i,j)})} \quad (10)$$

$$K_{(i,j)} = \alpha \cdot F_{(i,j)} - \beta \quad (11)$$

where $K_{(i,j)}$ represents the enhanced V component. To complete the process, a conversion back to RGB is achieved, and the resulting enhanced output is created. Figure 1 shows the developed algorithm diagram.

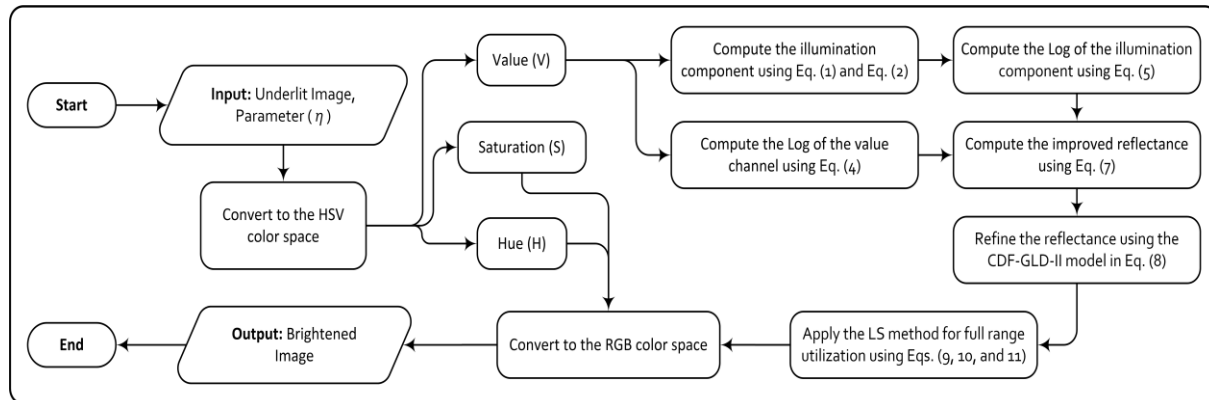


Figure 1. Diagram of the proposed algorithm.

3. RESULTS AND ANALYSIS

This part provides the outcomes and evaluates the performance of the developed algorithm with different archaeological images. The dataset of images was attained from three different sources. The first is unsplash.com, which was established in 2013 as a popular website with millions of free, high-resolution images. The second is pexels.com, a free website with over 3.2 million free stock images founded in 2014. Accordingly, more than two hundred images were collected from these two sources for this study. In addition, another dataset of images was collected from the UNESCO World Heritage Center, which can be reached at <https://whc.unesco.org/en/documents>, and used in this study as an additional dataset, especially for comparison purposes. The results demonstrated are of three types. The first is testing the developed algorithm with different η values, and the outcomes of this experiment are shown in Figure 2. The second is testing the developed algorithm with dissimilar archaeological images, and the outcomes of these tests are demonstrated in Figures 3, 4, and 5. The third is comparing the proposed algorithm with different existing algorithms, and the results of such action are shown in Figures 6, 7, and 8, and Tables 1 and 2.

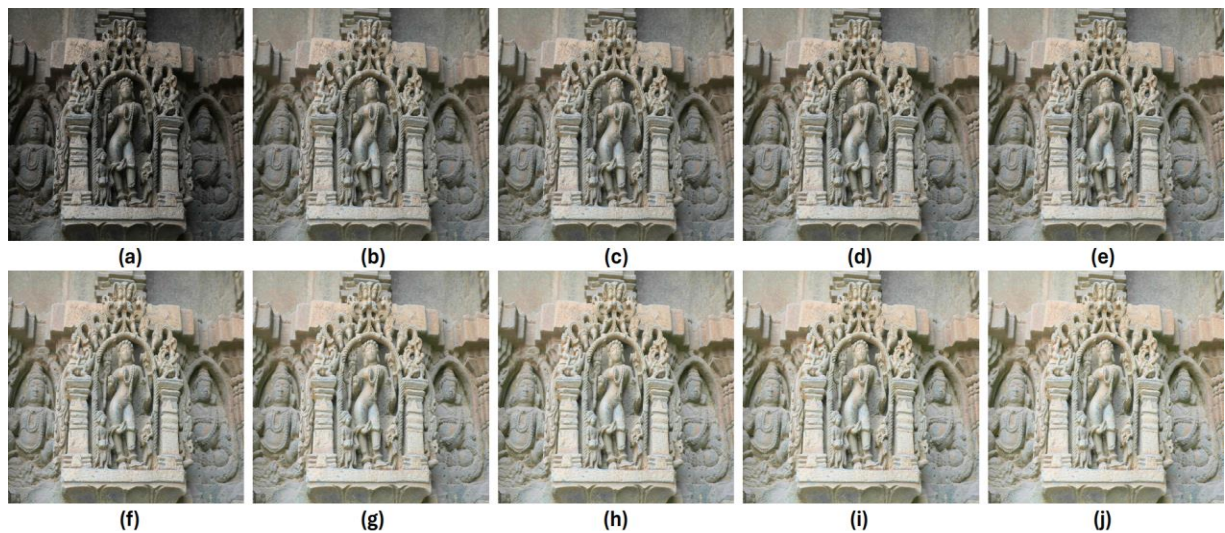


Figure 2. The illumination effect when changing the parameter (η). (a) unprocessed image; the others are processed with η with the value of: (b) 1; (c) 1.5; (d) 2; (e) 2.5; (f) 3; (g) 3.5; (h) 4; (i) 4.5; (j) 5.

Figure 2 demonstrates the effect of varying the value of η on illumination correction. It is noticed that it progressively improves the visibility of details and brightness. In the pristine image (a), the view looks dark, with darkness veiling the fine textures. As η rises from one (b) to five (j), the overall illumination improves, making previously veiled details better stand out. At lower values (b to d), the modifications are subtle, with an average rise in brightness while preserving a natural contrast. As η upsurges beyond 2.5 (e to h), the image becomes noticeably brighter, lowering the domination of shadows and slightly leveling local contrast. The improvement continues when η increases, where the output is perceived as somewhat uniformly brightened. The contrast is also enhanced progressively. This leads to revealing details in shadowed areas and gradually pronouncing the tonal variations. Increasing η improves illumination and visibility but calls for cautious tuning. This prevents unnecessary brightness increase that may affect the naturalness of the resulting image.

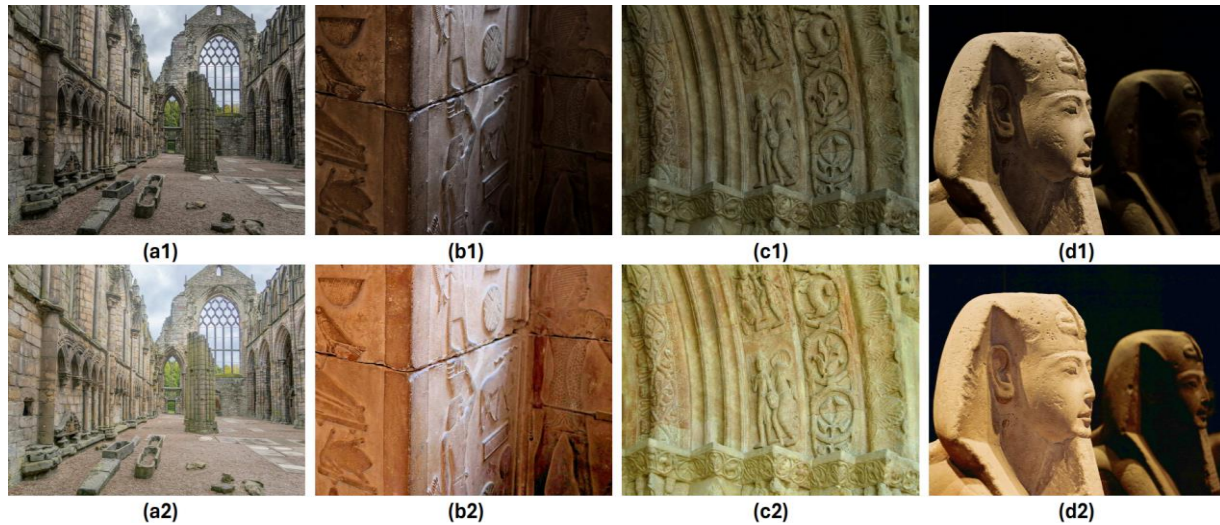


Figure 3. The empirical outcomes (**1st Set**): (a1-d1) images with low-light effect; (a2-d2) outcomes of the developed method with $\eta = (2, 4.5, 2, 3)$.

Figures 3 to 5 show the experimental results of various underlit images. The top row includes the unprocessed images, which are originally underlit. The bottom row contains the results after being processed via dissimilar η values. In the top row, the visibility is notably reduced due to a lack of detail, low lighting, and shadows. For example, Figure 4 (a1) appears noticeably dark, making it uneasy to see the statue details. Similarly, (d1) and (e1) have major differences between the bright and dark parts. This causes loss of details and texture information in shadowed parts. Moreover, in Figure 5, the images (b1, c1, f1) are also underlit and appear with less discernibility of textures and details. After employing the proposed algorithm to filter the images, they appeared with considerable improvement in lucidity and brightness. In addition, it preserved the naturalness of visual dynamics by balancing the tonal transitions.

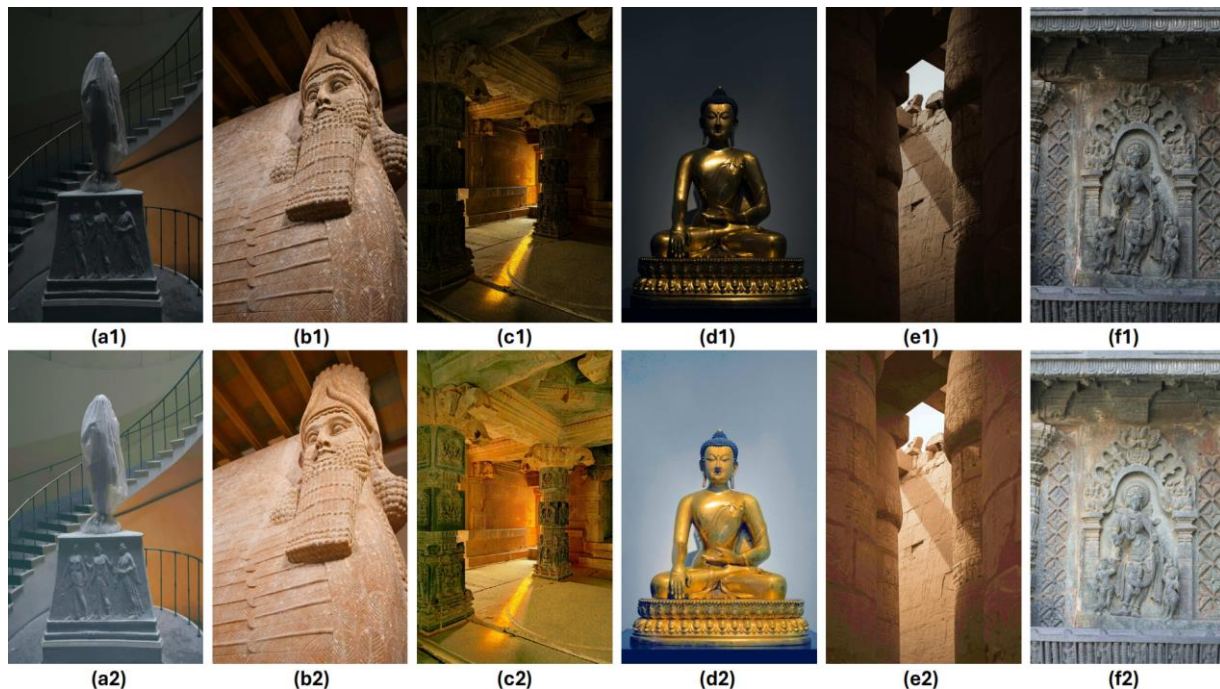


Figure 4. The empirical outcomes (**2nd Set**): (a1-f1) images with low-light effect; (a2-f2) outcomes of the developed method with $\eta = (2, 3.5, 4, 6, 5, 3)$.

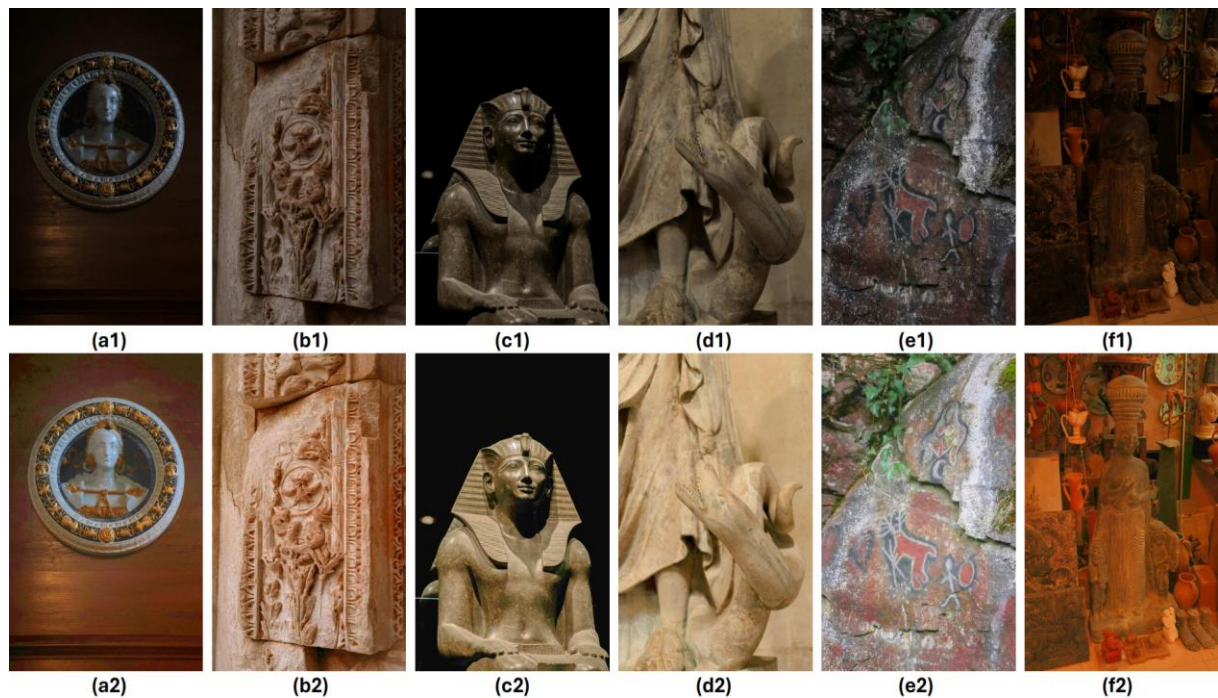


Figure 5. The empirical outcomes (**3rd Set**): (a1-f1) images with low-light effect; (a2-f2) outcomes of the developed method with $\eta = (2.5, 2.5, 2, 4, 3.5, 3.5)$.

The algorithm further improved the dim areas, causing the revelation of more latent details. It achieved that without extremely brightening the well-lit details and making the textures more pronounced. Accordingly, the distinct image elements became richer in detail in the surfaces and carvings, as well as retaining structural depth with balanced illumination. The choice of η values influences the enhancement level. In this context, lower values deliver mediocre illumination, and greater values yield a further pronounced appearance. In summary, the developed algorithm successfully improved the visibility and brightness in underlit photos. This enabled the recovery of dim details and enhanced illumination with natural structures. However, a severe increase in η could introduce an overexposed effect, making the resulting images appear slightly artificial in certain cases. Thus, carefully selecting an adequate η can lead to the desired results.

Figures 6 to 8 and Tables 1 and 2 show the comparison results and the assessments using lightness order error (LOE) [15] and runtimes (RT) in seconds. The LOE is a measure employed to determine the relativity of ordering lightness, comparing the local relative order of pixel brightness with the input dim image and its enhanced counterpart. If a pixel is brighter than the adjacent pixels in the original image, the same should be true in its improved version. It is a reduced-reference metric that does not require reference or ground truth images in the assessment process, making it practical in the scenario because it measures the average number of pairwise lightness order mismatches. The LOE outputs a numerical value, where lower values indicate that more natural lightness is achieved. Likewise, RT is used to evaluate the efficiency of algorithms by indicating how fast an algorithm can process an image, directly impacting the usability in different scenarios. Lower RT readings mean faster performances and lower computational cost, which is better. Moreover, a comparison with six methods, namely the original SSR, BCP [16], GB [17], PCA [18], SSF [19], and STF [20], with the analysis given accordingly.

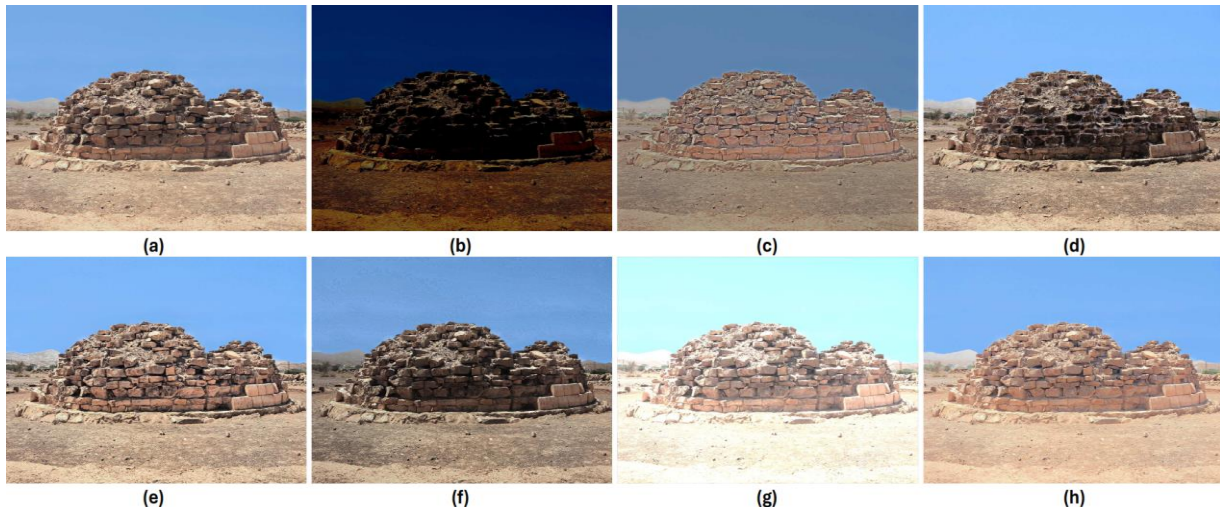


Figure 6. The comparison results (**Set 1**): (a) degraded image (2880×1920); the other photos are filtered with: (b) SSR; (c) BCP; (d) GB; (e) PCA; (f) SSF; (g) STF; (h) Developed algorithm.

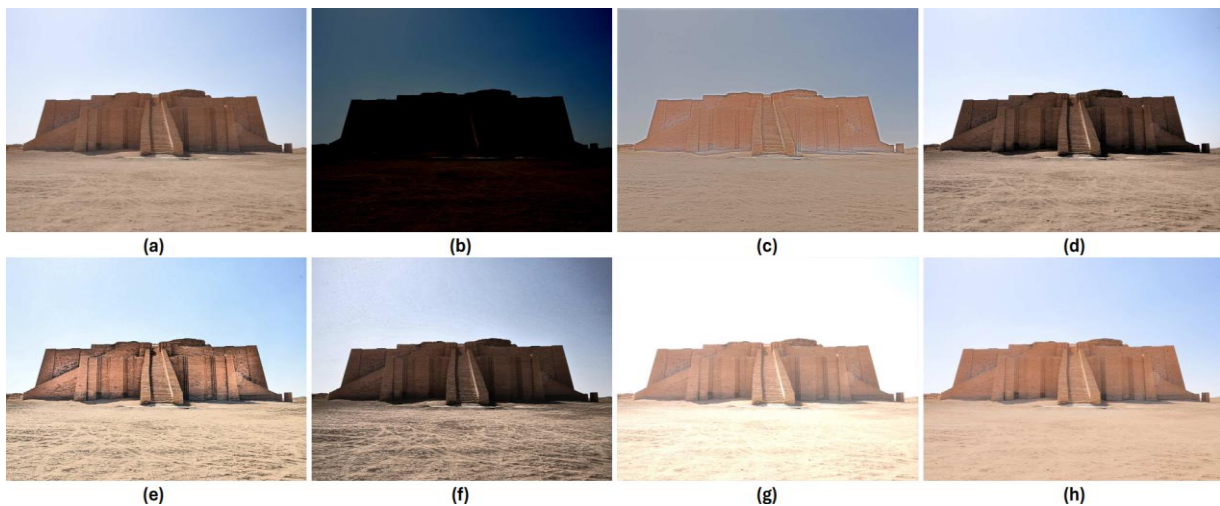


Figure 7. The comparison results (**Set 2**): (a) degraded image (4288×2848); the other photos are filtered with: (b) SSR; (c) BCP; (d) GB; (e) PCA; (f) SSF; (g) STF; (h) Developed algorithm.

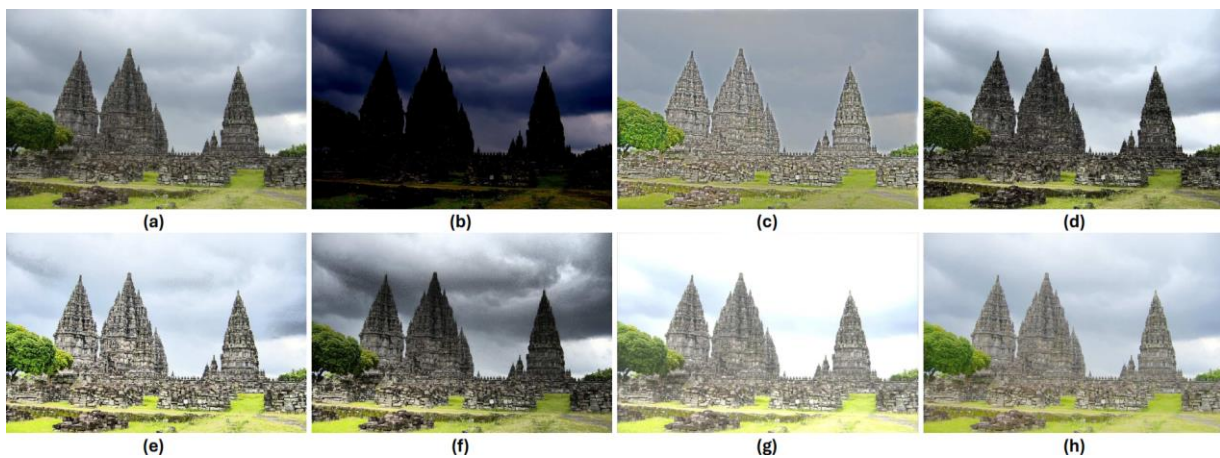


Figure 8. The comparison results (**Set 3**): (a) degraded image (2048×1290); the other photos are filtered with: (b) SSR; (c) BCP; (d) GB; (e) PCA; (f) SSF; (g) STF; (h) Developed algorithm.

The comparisons presented in Figures 6-8 and Tables 1-2 evaluate the performances of competing algorithms across three samples of unevenly illuminated images. The assessment considers both visual inspections and quantitative measurements based on LOE readings and RT. LOE indicates illumination consistency, while RT indicates computational intricacy. Together, these two methods provide insight into each algorithm's processing capabilities. At first, the SSR provided an overall dark appearance, with minor haloing visible in certain areas. Still, its average LOE score of 293.99 sanctions a tangible preservation of illumination consistency despite the overall dark appearance. It also averaged at 0.9498 seconds in RT, a relatively fast time.

Table 1. Recorded Runtimes ↓

<i>Methods</i>	<i>Figure 6</i>	<i>Figure 7</i>	<i>Figure 8</i>	<i>Average</i>	<i>Grade</i>
SSR	0.694008	1.818036	0.337458	0.9498	2 nd
BCP	12.927988	28.029931	5.816979	15.5916	6 th
GB	21.598537	11.436318	7.360658	13.4651	5 th
PCA	1.975552	3.261286	0.933943	2.0569	4 th
SSF	1.358085	2.766635	0.770920	1.6318	3 rd
STF	34.110362	75.773750	16.086356	41.9901	7 th
Proposed	0.618062	1.453809	0.322649	0.7981	1st

Table 2. LOE Scores ↓

<i>Methods</i>	<i>Figure 6</i>	<i>Figure 7</i>	<i>Figure 8</i>	<i>Average</i>	<i>Grade</i>
SSR	483.8235	188.5747	209.5718	293.99	2 nd
BCP	1255.8	2677.1	2680.0	2204.3	7 th
GB	981.2379	264.9516	374.1801	540.12	3 rd
PCA	436.5925	675.1889	971.4152	694.39	5 th
SSF	154.0168	528.8403	1004.2	562.35	4 th
STF	1028.1	1202.5	939.6471	1056.74	6 th
Proposed	250.0123	179.5745	155.8366	195.14	1st

The BCP delivered exceedingly and unnaturally bright results. Also, it presented obvious artificial illumination despite some visual clarity gains. This is reflected in its extremely high average LOE scores of 2204.3, which is the worst among all the competitors. It similarly represents serious illumination consistency distortion. Regarding RT, the BCP is computationally intensive, being the 2nd slowest with an average of 15.59 seconds. In terms of GB, the illumination remained irregular. Its average LOE of 540.12 is moderate, showing better consistency than BCP but weaker consistency than SSR. The average RT of 13.47 seconds is relatively high. Moving to PCA, it produced visually enhanced but unnatural

local contrast. This suggests deficient illumination correction in darker sections. Its average LOE score of 694.39 supports this moderate performance, while the mean RT of 2.06 seconds places it in mid-range. This makes it acceptable but not ideal. In the case of SSF, it weakly restored the visibility and introduced some filtration flaws. With a mean LOE of 562.35, it achieves fair fidelity. Its average RT of 1.63 seconds is competitive.

Besides, STF delivered a strong enhancement but caused visible flaws and abnormal brightness augmentation. The average LOE of 1056.74 reflected instability in illumination mapping. It is also the slowest algorithm, with a mean RT of 41.99 seconds. As for the proposed algorithm, it produced visually superior results. It delivered more natural tones, well-enhanced the dimmed areas, and maintained structural integrity without introducing an overexposure effect. Its lowest mean LOE reading of 195.14 demonstrated adequate illumination consistency achievement. Furthermore, it attained the fastest average RT of 0.798 seconds, proving both accuracy and computational efficiency. In summary, the comparative analysis demonstrated that the proposed algorithm achieved a satisfactory trade-off between visual fidelity and processing speed. Despite the inherent difficulties of this topic, it is completed by a non-complex algorithm that does not have a high computational cost. In contrast, methods like STF and BCP, despite certain visual gain, suffer from high illumination errors and long runtimes.

4. CONCLUSION

In conclusion, this study presented an improved SSR algorithm designed to enhance underlit archaeological images captured in uncontrolled environments. The classical SSR is modified by changing the subtraction process to estimate the reflectance with a more suitable one related to LIP. The reflectance is then further refined using two models. These modifications enabled the SSR to become better suited for archaeological use. The results show significant visual improvements when tested with dissimilar images. Parameter η is used to adjust brightness, and different values enable meticulous control over illumination. This ensured adaptability to different lighting conditions. Likewise, higher η values enhance brightness and reveal obscured features. Moreover, using moderate values balanced the enhancement with a naturalistic look, reducing overexposure and noise perceptibility. A comparison with different algorithms also confirmed that the developed algorithm can do a better job than many existing algorithms. Future work could explore further optimization of η parameters and integration with other image processing techniques to address other degradations, ensuring broader applicability.

REFERENCES

- [1] Olsen, B., & Pétursdóttir, Þ. (2014). *Ruin memories: materialities, aesthetics and the archaeology of the recent past*. Routledge.
- [2] Ding, D., Shi, F., & Li, Y. (2025). Low-illumination color imaging: Progress and challenges. *Optics & Laser Technology*, 184, 112553.
- [3] Huvila, I., Sköld, O., & Börjesson, L. (2021). Documenting information making in archaeological field reports. *Journal of Documentation*, 77(5), 1107-1127.
- [4] Darbari, P., & Kumar, M. (2022, May). Satellite image enhancement techniques: A comprehensive review. In *Proceedings of International Conference on Communication and Artificial Intelligence: ICCAI 2021* (pp. 431-447). Singapore: Springer Nature Singapore.
- [5] Zhang, Y., Guo, X., Ma, J., Liu, W., & Zhang, J. (2021). Beyond brightening low-light images. *International Journal of Computer Vision*, 129, 1013-1037.

- [6] Rockcastle, S., Danell, M., Calabrese, E., Sollom-Brotherton, G., Mahic, A., Van Den Wymelenberg, K., & Davis, R. J. L. R. (2021). Comparing perceptions of a dimmable LED lighting system between a real space and a virtual reality display. *Lighting Research & Technology*, 53(8), 701-725.
- [7] Rong, L., Zhang, S. H., Yin, M. F., Wang, D., Zhao, J., Wang, Y., & Lin, S. F. (2024). Reconstruction efficiency enhancement of amplitude-type holograms by using Single-Scale Retinex algorithm. *Optics and Lasers in Engineering*, 176, 108097.
- [8] McCann, J. J. (2017). Retinex at 50: color theory and spatial algorithms, a review. *Journal of Electronic Imaging*, 26(3), 031204-031204.
- [9] Yeonan-Kim, J., & Bertalmío, M. (2017). Analysis of retinal and cortical components of Retinex algorithms. *Journal of Electronic Imaging*, 26(3), 031208.
- [10] Li, J. (2013). Application of image enhancement method for digital images based on Retinex theory. *Optik*, 124(23), 5986-5988.
- [11] Basheer, O. A., & Al-Ameen, Z. (2024). Illumination enhancement of nighttime images using a regulated single-scale Retinex algorithm. *Jordanian Journal of Computers & Information Technology*, 10(2), 138-151.
- [12] Patrascu, V., & Buzuloiu, V. (2003, July). Color image processing using logarithmic operations. In *Signals, Circuits and Systems, 2003. SCS 2003. International Symposium on* (Vol. 1, pp. 133-136). IEEE.
- [13] Al-Ameen, Z. (2020). Improving the contrast of aerial images using a new multi-concept algorithm. *IEIE Transactions on Smart Processing & Computing*, 9(5), 353-364.
- [14] Al-Ameen, Z. (2020). Satellite image enhancement using an ameliorated balance contrast enhancement technique. *Traitement du Signal*, 37(2), 245-254.
- [15] Wang, S., Zheng, J., Hu, H. M., & Li, B. (2013). Naturalness preserved enhancement algorithm for non-uniform illumination images. *IEEE Transactions on Image Processing*, 22(9), 3538-3548.
- [16] Fu, X., Zeng, D., Huang, Y., Ding, X., & Zhang, X. P. (2013, December). A variational framework for single low light image enhancement using bright channel prior. In *2013 IEEE Global Conference on Signal and Information Processing* (pp. 1085-1088). IEEE.
- [17] Tanaka, M., Shibata, T., & Okutomi, M. (2019, January). Gradient-based low-light image enhancement. In *2019 IEEE International Conference on Consumer Electronics (ICCE)* (pp. 1-2). IEEE.
- [18] Singh, N., & Bhandari, A. K. (2021). Principal component analysis-based low-light image enhancement using reflection model. *IEEE transactions on instrumentation and measurement*, 70, 1-10.
- [19] Demir, Y., & Kaplan, N. H. (2023). Low-light image enhancement based on sharpening-smoothing image filter. *Digital Signal Processing*, 138, 104054.
- [20] Sundari, K. S., & Keerthi, B. S. (2024). Enhancing low-light images using Sakaguchi type function and Gegenbauer polynomial. *Scientific Reports*, 14(1), 29679.