

Improving Illumination Uniformity for Archaeology-Related Images Using a Refined Type-II Fuzzy Algorithm

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Abstract

Archaeology-related images are often captured in ambient or non-ideal lighting, leading to illumination non-uniformity. It is a condition in which illumination is unevenly distributed across the image, causing some regions to appear dark while others appear bright. This effect hides details in the dark regions, reducing the usability of such images for analysis, documentation, archiving, display, and 3D modeling. Hence, a refined type-II fuzzy (RTF) algorithm is introduced to improve illumination uniformity. RTF improves uniformity by suppressing bright regions, while boosting dark regions. The experimental results demonstrate that RTF successfully performed its task, delivering better illumination harmonization in the processed images. This allowed for better perception of darkened details and confirmed that RTF can work across different illumination scenarios and scenes.

Introduction

One of the best tools for documenting, archiving, modelling, and preserving cultural heritage is digital images [1]. It allows researchers to capture and store the visual attributes of various archaeology-related scenes with precision [2]. Among the various degradations that reduce the utility and visual quality of such images, non-uniform illumination (NUI) stands out as a pervasive and consequential effect [3]. It directly undermines the detail-visibility and readability of affected images [4]. NUI is a condition in which illumination is unevenly allocated across the image, resulting in certain regions appearing dark, while other regions appear well-lit [5]. NUI occurs due to ambient or non-ideal lighting, environmental factors, and incorrect camera settings.

Accordingly, it is rare to achieve the isotropic, controlled lighting conditions needed when photographing in chambers, trenches, museum rooms, enclosed or outdoor settings. The collective outcome is a scene in which dimmed regions coexist with bright highlights in the same image. This suppresses fine details in the image, which many constitute the primary informational content of the photographed scene [6]. Addressing this effect is not a peripheral issue but a prerequisite for the integrity of captured archaeological images. NUI can affect in different directions. When building 3D models from images, shadowing is introduced in the model. For archiving, display, and documentation, more faithful representations of captured scenes are needed, since the NUI effect might cause these images to fail to meet the expected requirements.

Improving illumination uniformity is therefore essential to ensure the usability of archaeological images across the various spectrum of applications. Despite the significance of this need, existing algorithms for illumination uniformity exhibit a range of limitations. Histogram-based methods, such as CLAHE [7], may cause shadowing or over-enhancement. Retinex-based techniques [8] are more widely used but are prone to halo artifacts and contrast issues. Deep learning-based approaches [9] have become more

research-focused in recent years but require large or well-controlled ground-truth datasets for training and testing, which may be unavailable in many scenarios. This indicates a key research gap: there are not many available customized algorithms to improve the illumination uniformity of archeological images.

To deliver a solution for NUI, other processing concepts are considered. Fuzzy concepts have been applied in many real-world domains, yet they remain underexplored in archaeology. Among these concepts, type-II is a largely underexplored framework that can offer richer illumination uniformity. It utilizes multi-membership functions that can suppress well-lit areas while boosting under-lit regions inside a unified framework, which, if properly developed, can deliver adequate illumination uniformity. This motivates the development of a type-II fuzzy algorithm that can operate without large datasets, training concept, or scene-specificity.

Accordingly, the type-II fuzzy concept should be developed to be a scene-generalized algorithm that restores illumination uniformity while preserving other attributes. To address this issue, the primary objective is to introduce a refined type-II fuzzy (RTF) algorithm that corrects illumination in a natural, realistic way and evaluate it across diverse images to validate its effectiveness under diverse conditions and dissimilar scenes. The remaining parts of this study are organized as follows: Section 2 presents the developed RTF algorithm, beginning with the original form, then proceeding to its developed counterpart. Section 3 reports the outcomes and analysis related to experiments and comparisons. Section 4 concludes the study by summarizing key findings.

Proposed Algorithm

The original type-II fuzzy algorithm was presented in [10] for medical applications to improve the contrast. It works by utilizing only four equations. To begin, the input image (q) is fuzzified as:

$$u = \frac{q - \min(q)}{\max(q) - \min(q)} \quad (1)$$

where $\min$ and $\max$ are the lowest and highest values in q , and u is a fuzzified image. Next, the upper p and lower l intervals of the Hamacher t-conorm, which is the fuzzy membership function, are computed in the following manner:

$$l = (u)^{\frac{1}{\gamma}} \quad (2)$$

$$p = (u)^{\gamma} \quad (3)$$

where γ signifies the enhancement factor satisfying $0 < \gamma \leq 1$, in that a higher value leads to more enhancement. After that, the Hamacher t-conorm (t), which is mainly used to combine the membership values nonlinearly, is determined as follows:

$$t = \frac{p + l + (\psi - 2) \cdot p \cdot l}{1 - (1 - \psi) \cdot p \cdot l} \quad (4)$$

where ψ represents the mean of image u , t represents the algorithm output, and $(\cdot)$ is a multiplication operator. This algorithm is structurally non-complex, direct, and lightweight. These features make it promising for further development. Thus, this algorithm is refined to be well-suited for improving illumination uniformity for archaeology-related images. The proposed refined type-II fuzzy (RTF) algorithm starts by converting the input image from RGB to HSV (i.e., hue (H), saturation (S), and value (V)) color space, processing only the V channel. When enhancing illumination uniformity, the V channel is processed because it directly signifies the image illumination or brightness. By making the intensity values more uniform, the overall appearance becomes visually attractive. Hence, channel V is initially processed by three equations, acting as an initial illumination-equalization phase, in the following manner:

$$b_1 = \log(V + \varepsilon) \quad (5)$$

$$b_2 = \log\left(\frac{V + \varepsilon}{1 + \sqrt{1 - V}}\right) \quad (6)$$

$$w = \left(\frac{b_1}{1 + (1 - b_1)}\right)^2 - (1 - b_2) \quad (7)$$

where w represents the output of the first equalization phase, and a small value ($\varepsilon = 0.01$) is added to the log input to avoid $\log(0) \rightarrow \infty$. In this context, logarithmic transforms are commonly used because they expand low-illumination values while compressing high-illumination values. This improves the dark regions, attenuating shadows and enhancing illumination uniformity. Since a single transformer is insufficient to achieve the needed enhancement [11], two transformers are used, the ones in Eq. (5) and Eq. (6). As for Eq. (7), it performs nonlinear refinement using the values of equations 5 and 6. This increases the low-to-mid intensity ranges while suppressing very high values, effectively reallocating intensity levels. Next, a modified type-II fuzzy algorithm is applied to update illumination uniformity. Accordingly, w is fuzzified using Eq. (1). Using the fuzzified output denoted as $(\tilde{u})$, the new upper p_2 [12] and lower l_2 [13] intervals are mathematically computed, using the following equations:

$$l_2 = \log(\exp(\tilde{u}) + \varepsilon)^2 \quad (8)$$

$$p_2 = 1 - \exp\left(-\arcsin\left(\tilde{u}^{(2-\lambda)}\right)\right) \quad (9)$$

where λ signifies the new enhancement factor satisfying $\lambda > 0$, in that a higher value reduces illumination. Eq. (8) is a smooth rectifier function, which boosts low-valued intensities, while Eq. (9) is a modified exponential distribution, which compresses extremely bright areas. After that, the new Hamacher t-conorm (t_2) is computed using the following formula:

$$t_2 = \frac{p_2 + l_2 + (\sigma - 2) \cdot p_2 \cdot l_2}{1 - (1 - \sigma) \cdot p_2 \cdot l_2} \quad (10)$$

where σ represents the variance of $(\tilde{u})$, and it is used instead of the mean because the mean delivers a high value, in that if used, it would further amplify the illumination in the highly illuminated areas, which is undesirable. Next, a defuzzification process is applied, as given in the subsequent formula [14]:

$$\tilde{V} = (\max(t_2) - \min(t_2)) \cdot t_2 + \min(t_2) \quad (11)$$

where $\tilde{V}$ represents the enhanced V channel, and finally, the data are transformed from $HS\tilde{V}$ to RGB to deliver the output image.

Result & Analysis

This section provides the performance analysis of the study. To begin with, the used dataset contains 300 images, self-collected from <https://unsplash.com>. This website is one of the largest sites that offers high-quality, free images contributed by photographers worldwide. The images are used for empirical and comparison validations. Accordingly, Figures 1 and 2 show the results of the proposed algorithm. Moreover, a comparison with eight modern algorithms is made, including the following: LIME [4], LightenNet [15], fractional-order fusion (FOF) [16], fast bright-pass bilateral (FBPB) [17], principal component analysis (PCA) [18], sharpening-smoothing (SS) [19], ACGC [20], and IMS [21]. In addition, the comparison is evaluated using lightness order error (LOE) [22], perception-based image quality evaluator (PIQE) [23], and processing time (PT) [24]. LOE measures the consistency of illumination, with lower values representing more visually consistent enhancement. PIQE measures perceptual distortions, with lower values indicating better perceived quality. PT measures computational time and reflects the algorithm efficiency, with lower values signifying faster performance. After performing the comparisons and evaluations, the required analysis is provided. Lastly, this section ends with key concluding remarks.

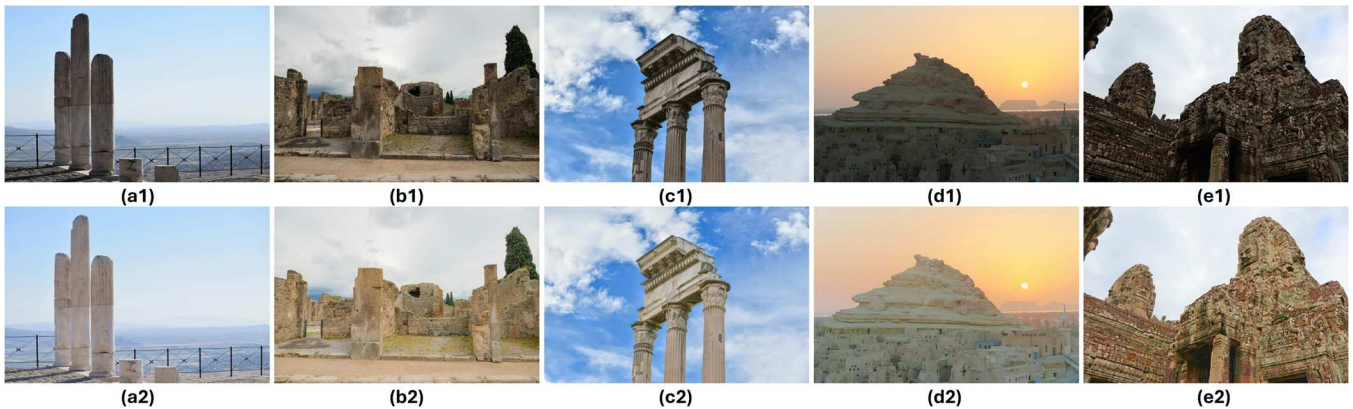


Figure 1. Experimental results (Group 1). (a1-e1) Original images. (a2-e2) Results of the RTF algorithm.

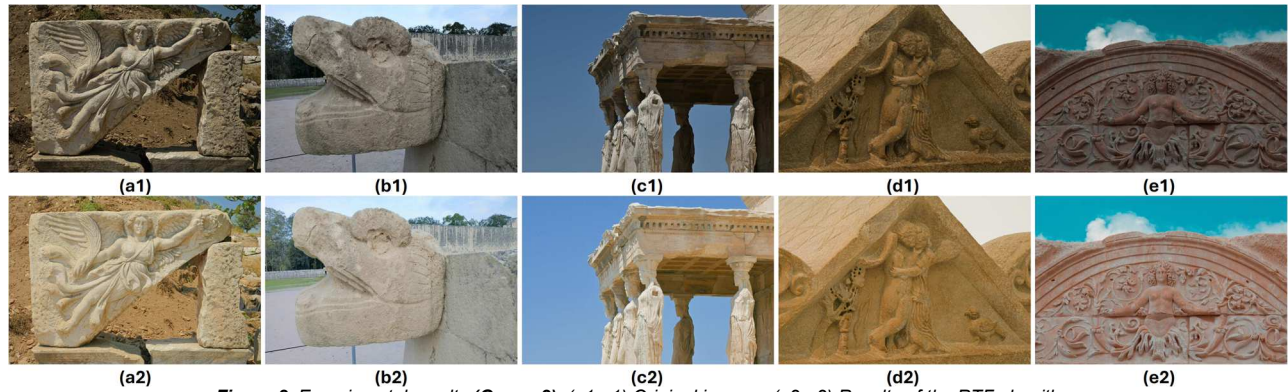


Figure 2. Experimental results (Group 2). (a1-e1) Original images. (a2-e2) Results of the RTF algorithm.

The comparison outcomes are provided in Figures 3 to 6, while the recorded evaluation scores are given in Tables 1 to 3. The experimental results in Figures 1 and 2 demonstrated that RTF significantly enhanced illumination uniformity, reducing shadows and overexposure. Compared to the original version, the processed images also exhibited improved tonality. This allowed structural details and textures to become more distinguishable without introducing processing artifacts. In addition, color representation became more balanced and natural, avoiding color distortions. In this context, the visibility trait is markedly improved, as dimmed regions are revealed with greater clarity. This facilitates better analysis and interpretation. As for acutance, it remained unchanged, similar to the original ones. Altogether, the enhanced images present

a more informative and visually coherent appearance, and the scenes are perceptually more consistent, indicating the competence of RTF. The comparison outcomes presented in Figures 3 to 6 and Tables 1 to 3 show significant differences among the compared methods in dissimilar image attributes. The visual observations are supported by the evaluation methods used. Beginning with LIME, it provides a high illumination enhancement and reveals details in dimmed areas. Still, the resulting images suffer from over-correction and unnecessary enhancement in already brightened areas, losing their natural appearance. This is why it scored relatively high on LOE (764.25) and moderate on PIQE (32.26) due to halo artifacts, extra illumination, and unnatural saturation. Still, it remains computationally efficient, with an average PT of 7.06 seconds.

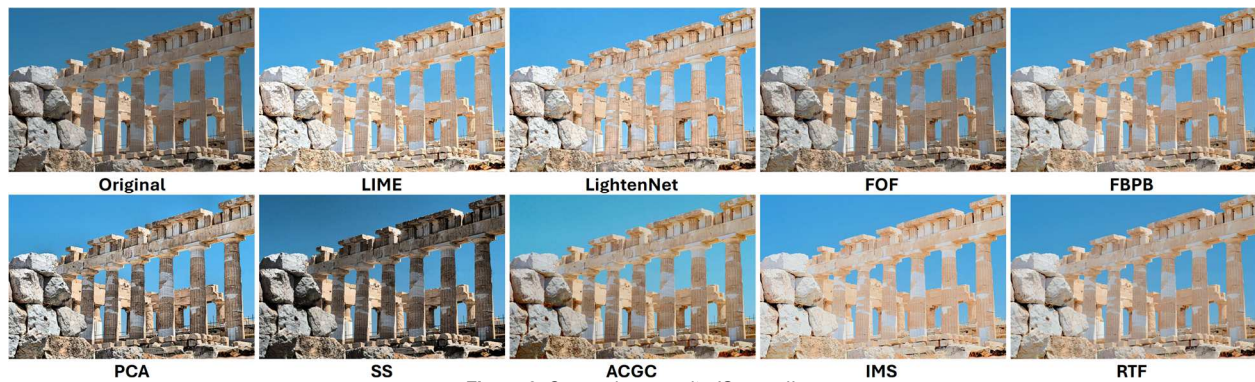


Figure 3. Comparison results (Group 1).



Figure 4. Comparison results (Group 2).

LightenNet provided noticeable enhancement for dark regions but delivered extra illumination, along with inconsistent visual quality and visible processing errors. It recorded below-average in LOE (928.89), indicating significant disruption in illumination uniformity. Still, it delivered a competitive average score (ranking 3rd) with PIQE due to artificial tonal transitions and deficient color

quality. Despite that, it incurred a very high computational cost with an average PT of 266.76 seconds. FOF produced visually enhanced results, particularly in dimmed areas with marked detail recovery. This helped to improve the overall scene visibility. Metric-wise, it achieved competitive scores, ranking 3rd in LOE with an average of 183.92.



Figure 5. Comparison results (Group 3).

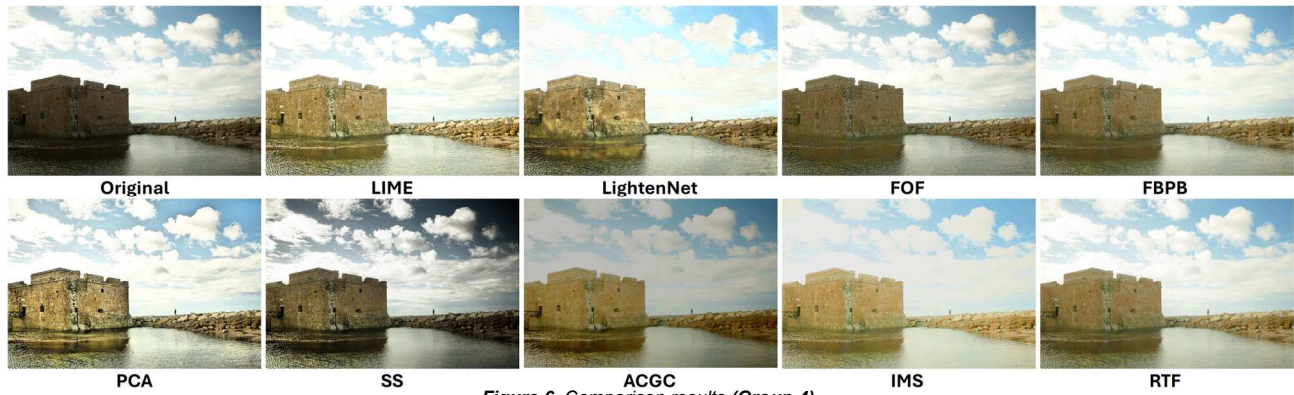


Figure 6. Comparison results (Group 4).

However, it delivered deficient tonality, causing loss of natural appearance. This explains the less favorable PIQE readings, ranking 4th with an average of 31.01. This affected the color production, resulting in less colorfulness. The major downside of FOF is its PT, which was extremely slow, recording the highest average PT of 513.46 seconds. Going to FBPB, it demonstrated strong enhancement capability in illumination consistency. The resulting images have improved illumination distribution and enhanced the dimmed regions. This justifies its ranking 2nd in LOE with an

average score of 177.17. However, it sometimes increases illumination in well-lit regions and may also slightly affect the contrast. These observations are reflected in the PIQE below-moderate score (32.37). As for color quality, it maintained acceptable chromatic balance. In terms of PT, it required high componential time, averaging at 50.59 seconds, limiting its practicality despite its capabilities. PCA showed acceptable brightness enhancement, but struggled to maintain illumination consistency and perceptual naturalness.

Table 1: LOE_↓ readings.

#	Algorithms	Figure 3	Figure 4	Figure 5	Figure 6	Average	Rank
1	LIME	625.9563	773.2660	694.8613	962.9181	764.250425	7 th
2	LightenNet	1016.0	674.3937	958.4921	1066.7	928.89645	8 th
3	FOF	169.1266	139.6860	289.4832	137.3917	183.921875	3 rd
4	FBPB	293.6089	140.1337	175.5084	99.4400	177.17275	2 nd
5	PCA	575.4139	646.0869	554.1508	765.0347	635.171575	6 th
6	SS	358.9124	692.8555	447.2408	727.6165	556.6563	4 th
7	ACGC	728.7118	565.0752	430.0708	567.9821	572.959975	5 th
8	IMS	1146.1	1209.8	821.8229	1790.1	1241.955725	9 th
9	RTF	182.1061	149.7922	170.1618	59.3707	140.3577	1 st

Table 2: PIQE↓ readings.

#	Algorithms	Figure 3	Figure 4	Figure 5	Figure 6	Average	Rank
1	LIME	29.3517	17.9877	60.5581	21.1693	32.2667	5 th
2	LightenNet	28.8021	17.9312	58.6526	17.7006	30.771625	3 rd
3	FOF	15.3506	18.5783	61.6344	28.5058	31.017275	4 th
4	FBPB	29.9458	17.7916	59.3567	22.3862	32.370075	6 th
5	PCA	27.1315	27.1315	56.0861	23.1115	33.36515	9 th
6	SS	31.1563	18.5968	52.6491	29.0621	32.866075	8 th
7	ACGC	28.2311	18.9657	57.5345	24.9022	32.408375	7 th
8	IMS	27.1611	16.9648	56.2794	21.9122	30.579375	2 nd
9	RTF	21.2727	19.0734	55.7253	23.3935	29.866225	1 st

Table 3: PT↓ readings.

#	Algorithms	Figure 3 5928×3941	Figure 4 5364×4000	Figure 5 3888×2592	Figure 6 6000×4000	Average	Rank
1	LIME	8.397306	7.634665	3.613076	8.627641	7.068172	2 nd
2	LightenNet	290.680938	334.448934	130.478098	311.461791	266.7674403	8 th
3	FOF	513.771135	545.660854	256.142360	738.274634	513.4622458	9 th
4	FBPB	54.191578	57.545469	27.077445	63.555216	50.592427	7 th
5	PCA	11.932114	8.972779	4.697810	9.473445	8.769037	4 th
6	SS	11.384758	9.471314	3.537211	9.334059	8.4318355	3 rd
7	ACGC	30.129572	24.814960	10.318135	25.618249	22.720229	6 th
8	IMS	12.475413	11.728153	4.392485	13.240925	10.459244	5 th
9	RTF	4.476578	4.198493	1.975815	4.663501	3.82859675	1 st

Visually, the resulting images revealed brightness amplification and increased shadowing. This aligns with its high LOE score of 635.17, showing marked deviations in illumination consistency. In PIQE, it ranked lowest due to the visual artifacts generated. Despite that, it delivered above-moderate performance in PT, averaging at 8.76 seconds. SS enhanced the dimmed regions but generated artifacts, increased shadowing, and artificial appearance. However, its performance varied across the comparison images, as some results appeared under-enhanced. This inconsistency is reflected in its LOE score (ranking 4th) with an average of 556.65. The generated artifacts severely affected its average PIQE score, ranking 8th among the competitors. In PT, it maintained a relatively low time complexity, averaging at 8.43 seconds.

ACGC delivered results with deficient contrast, slight color cast, and lack of illumination uniformity. That's why it scored 572.95 in LOE, ranking 5th among the competitors. In PIQE, it performed poorly due to the generated artifacts. PT-wise, it achieved below-moderately, averaging at 22.72 seconds. IMS showed the weakest LOE performance among the competitors. The illumination produced by this algorithm is unnatural, causing certain highlights to be attenuated. However, it did not generate visual artifacts, scoring 2nd best with PIQE. Although it performed favorably on PIQE, the overall visual quality remains compromised owing to perceptual effects, including illumination distortions, unnatural transitions, and unrealistic colors. Computationally, it performed moderately according to PT, averaging at 10.45 seconds. Moving to the proposed RTF algorithm, it exhibited visually convincing results.

They reveal balanced illumination, effectively brightening darkened areas without overexposure. RTF also preserved structural details while maintaining realism and natural tonality, with limited visible artifacts. This is validated by scoring best in LOE and PIQE. Moreover, color quality remained natural, avoiding color cast and oversaturation. Another major benefit of RTF is its pronounced computational efficiency, achieving the lowest PT reading of 3.82

seconds. The comparative analysis showed that visual quality assessment could not be achieved using a single measure. Different aspects should be considered to determine the favorability of an algorithm. Accordingly, FOF and FBPB exhibited strong enhancement capabilities in illumination consistency, but they suffer from either high computational cost or the generation of perceptual artifacts. Less complex methods, such as SS, PCA, and LIME, offer faster execution but compromise naturalness. Deep-learning algorithms such as LightenNet improve visibility but over-lit in some cases, and require high processing time. Thus, RTF represents a balanced practical solution among the competing algorithms for archaeological applications.

Conclusion

This study introduced the RTF algorithm to improve illumination uniformity for archaeology images. RTF has a non-intricate structure and a few computations. Likewise, it can handle different lighting scenarios without introducing artifacts. RTF was tested with various images, having different sizes, lighting levels, scenes, and structures. It showed the ability to process these images effectively, validating its efficiency. Making the illumination more uniform significantly improves the visual appearance and interpretability, increasing the value of archaeology images for analysis, documentation, archiving, display, and 3D modeling. Moreover, this work emphasizes that well-designed algorithms can deliver adequate results, highlighting the importance of tailored image processing algorithms in cultural heritage preservation. Future direction includes further developing RTF to be completely automatic by computing λ using an innovative approach.

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