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ADVANCING COLOR MANAGEMENT IN NEURAL RADIANCE FIELDS

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ABSTRACT

In the exploration of color management within Neural Radiance Fields (NeRFs), this study bridges the gap between the photorealism of computer graphics and the consistency of color perception across varying devices and lighting conditions. Acknowledging the transformative impact of NeRFs in digital imagery, the research confronts the challenge of advanced color management by harnessing deep learning to render intricate details with high fidelity. The study de-ploys a range of digital cameras, profiling their color responses using sophisticated software, to inform the rendering process of NeRFs, ensuring an accurate representation of real-world colors. The methodology includes the meticulous selection of cameras based on sensor characteristics, resolution, and color sensitivity, followed by the calibration against standardized color charts. Scene composition and image capture are tailored to encompass a spectrum of colors, and the captured data serve as input for the NeRF processing, which undergoes training with a customized algorithm to fine-tune color interpretation. The results are indicative of the value of camera profiling, showing a marked improvement in color accuracy, particularly in high dynamic range (HDR) scenarios. Across different cameras and lighting conditions, the NeRF renders with pro-filed inputs yielded significantly lower Delta E values, suggesting closer alignment with the ac-tual scenes. Conclusively, the integration of camera profiling into NeRFs enhances the realism of digital representations, promising applications in various domains where color precision is paramount. The study underscores the need for further optimization to address the computation-al demands introduced by camera profiling and points to potential future synergies with AI and machine learning to streamline the process. The findings establish a foundation for ongoing advancements in digital rendering, aiming for even greater levels of color accuracy and user immersion in computer graphics.

Keywords: Neural Radiance Fields; Color Management in Digital Rendering; Camera Profiling.

INTRODUCTION

The advent of Neural Radiance Fields (NeRFs) has marked a transformative era in the domain of computer graphics and visual representation [1,2]. As a representation model for capturing and rendering 3D scenes, NeRFs uniquely synthesize novel viewpoints with remarkable precision and photorealism. Leveraging deep learning techniques, NeRFs interpolate light and color in a spatially continuous volumetric scene, enabling an unprecedented level of detail and realism in digital imagery [3].

However, with the expansion of NeRF capabilities, a critical challenge emerges: the need for advanced color management. Color management in NeRFs is crucial for ensuring the accuracy and consistency of color reproduction across diverse viewing conditions and devices. Its fundamental objective is to maintain the fidelity of color information, a pivotal factor in preserving the artist's intent and ensuring a uniform visual experience [4].

This paper delves into the emerging challenges and innovative solutions in color management within Neural Radiance Fields. It underscores the significance of this aspect in the broader context of NeRF technology, proposing new methodologies and frameworks that can revolutionize color processing and perception in digitally rendered environments.

The exploration begins with a foundational understanding of the current state of NeRF technology, focusing on its color rendering capabilities. This includes a review of existing methodologies and the inherent limitations that necessitate a more robust approach to color management. Novel techniques and approaches designed to enhance color fidelity in NeRF-generated imagery are introduced, critically analyzed for their effectiveness and potential implications in the field of computer graphics and beyond [5-7].

In summary, this introduction sets the stage for a comprehensive discussion on the evolution of color management in Neural Radiance Fields. By addressing current challenges and introducing groundbreaking solutions, this paper aims to contribute significantly to the advancement of NeRF technology, paving the way for more accurate, consistent, and visually stunning digital imagery.

MATERIALS AND METHODS

2.1 Camera Selection and Profiling Process

The camera's primary role is to accurately capture tri-chromatic channel values which, through linear transformation, can approximate the CIE standard observer XYZ values. This requirement is based on the need to digitally reconstruct colors with fidelity. The camera's sensor should ideally mimic the color sensitivity of the human eye, aligning with the standard observer color matching functions. However, due to practical manufacturing constraints and the necessity for camera sensors to maintain high sensitivity under low light conditions, an exact match with the standard observer's response is not feasible.

Most camera sensors are designed to capture red, green, and blue channels, corresponding broadly to the sensitivity of human vision. This enables the conversion of captured RGB data into XYZ values, aligning closely with the perceptual color space of a standard observer. Although this conversion is a linear process, the correlation is rarely direct due to the distinct spectral sensitivities of camera filters compared to the human eye. Nonetheless, with appropriate profiling and calibration, these RGB values can be transformed to yield a reliable approximation of XYZ, enabling effective color reproduction in digital renderings. we can with a straight linear conversion get close to the standard observer's XYZ values. This is a formula for calculating the value of XYZ:

$$X = R * M1{,}1 + G * M1{,}2 + B * M1{,}3 \quad (1)$$

$$Y = R * M2{,}1 + G * M2{,}2 + B * M2{,}3$$

$$Z = R * M3{,}1 + G * M3{,}2 + B * M3{,}3$$

The selection and profiling of cameras is a critical step in this study, as it establishes the baseline for color accuracy in the NeRF rendering process. A range of digital cameras with varying sensor sizes, resolutions, and color sensitivities are carefully chosen to represent the diversity typically encountered in digital imaging. Table 1 lists the specifications of the selected cameras.

Table 1: Features of the Cameras used for the Experiment.

	Panasonic LX-100 mk2	**Apple iPhone 12 Pro**	**LG V40**
Sensor type	MOS	CMOS	CMOS
Camera effective pixels Sensor Size Image Resolution Pixel Size Focal length	17 MP 4/3 inch 4736 x 3552 3.64µm f = 10.9 – 34mm	12 MP 1/3.4 inch 4032 x 3024 1.4µm f = 26mm	12 MP 1/3.4 inch 4032 x 3024 1.4µm f = 27mm

Each camera is then subjected to a comprehensive profiling process. This process includes capturing images of standardized color charts under controlled lighting conditions to map each camera's color response accurately [8]. Lumariver Profile Designer v 1.0.6 software was used in conjunction with X-rite's ColorChecker Passport to create sophisticated profiles for each camera and lighting condition [9]. These profiles contain essential data about how each camera interprets different colors and are used to inform the NeRF rendering process, ensuring that the system accurately replicates the camera's color perception. The meticulous nature of this profiling process is crucial for the success of the study, as it directly impacts the fidelity of color reproduction in the subsequent NeRF-rendered images. Figure 1 shows the camera profiling workflow in this study.

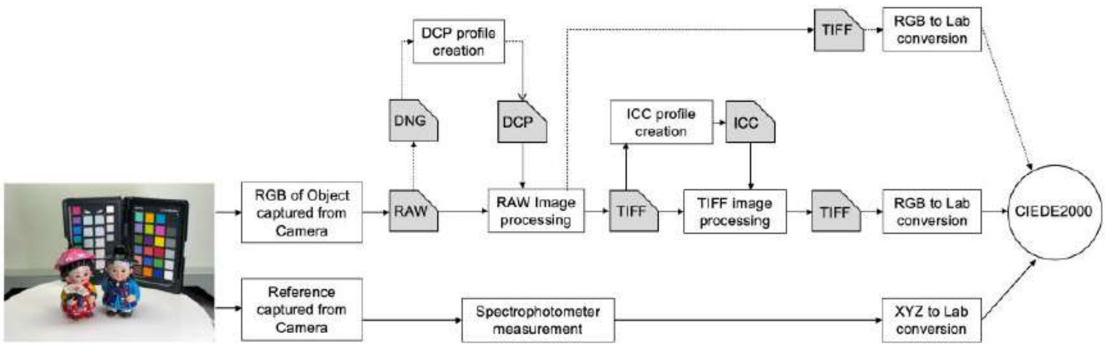

Figure 1: Camera Profiling Workflow.

2.2 Scene Composition and Image Capture

For this research, we select objects that can express a wide range of colors, saturation, and brightness to test the capabilities of camera profiling in the context of neural radiance fields. We also illuminate the scenes under different lighting conditions to simulate real-world scenarios. Images captured from these scenes using the profiled camera constitute the dataset for NeRF processing. This dataset plays a pivotal role in ensuring the robustness of our findings by providing a comprehensive basis for evaluating the effectiveness of camera profiling in different scenarios. To generate a dataset that accurately reflects the complex interplay of lighting, texture, and color in real-world environments, it is important to pay attention to the details of scene composition and image capture. Figure 2 shows a controlled environment shot of an object moving at a fixed speed on a turntable with selected colors, textures, and saturation.

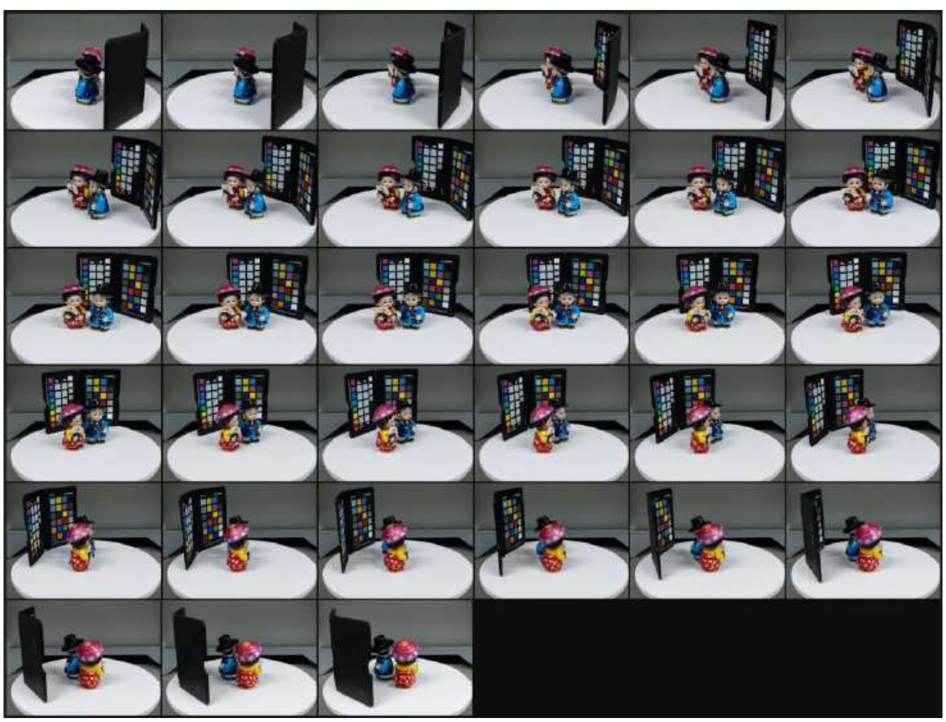

Figure 2: Controlled Image Capture with Turntable

2.3 NeRF Configuration and Processing

The images captured in this step are output as a dataset of 226 images that are preprocessed using the camera profile, and all of these images are posed using COLMAP [10]. 204 images are set as the training dataset and 22 images are set as the evaluation dataset to be trained using the Nerfacto algorithm [11].

This involves fine-tuning the color values of the images to accurately interpret the color information encoded in the camera profile. An image from each of the profiled cameras is used as input, and the NeRF system renders the scene accordingly. This process is critical to evaluating the effectiveness of camera profiling in NeRF because it directly affects the color accuracy and realism of the rendered image [12]. The construction and processing steps play a key role in understanding the impact of different camera profiles on the final NeRF output. For training, we used the NeRFStudio framework as shown in figure 3.

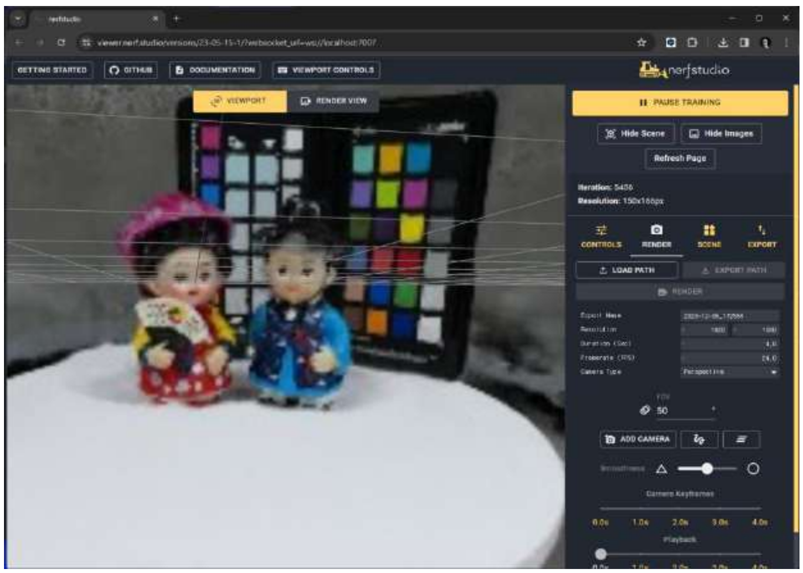

Figure 3: NeRF training with Nerfacto algorithm from NeRFStudio

2.4 Colorimetric Analysis for Rendered Images

The colorimetric analysis of the NeRF-rendered images is a critical component of the study. This process involves using standardized color metrics to quantitatively evaluate the color fidelity of the images rendered from the profiled camera inputs. Specifically, the Delta E metric, which measures the perceptual difference between two colors, is utilized to compare the rendered images against the original scenes [13]. This comparison helps in objectively assessing the effectiveness of camera profiling in improving color accuracy [14]. The analysis is meticulous, ensuring that each rendered image is evaluated under varying conditions to understand the full impact of camera profiling. This step is essential for quantifying the enhancements in color accuracy and fidelity achieved through the integration of camera profiling in the NeRF process.

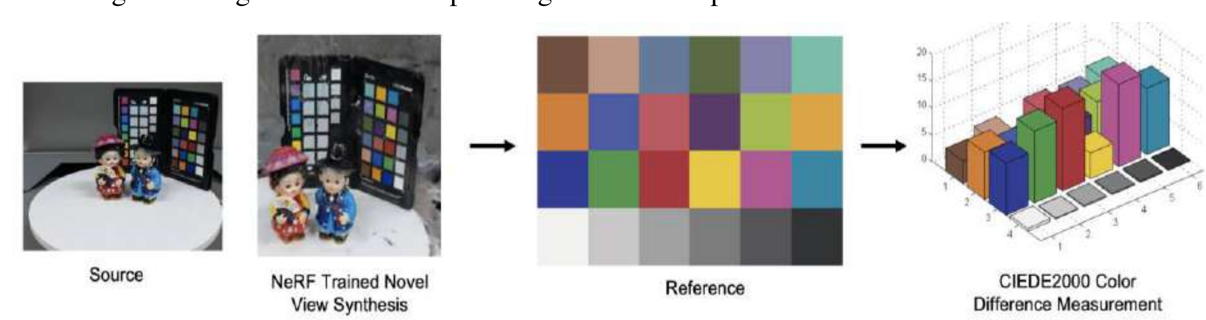

Figure 4: CIEDE2000 Color Difference Measurement Workflow

The CIEDE2000 color difference metric was employed to assess the accuracy of the NeRF's color rendering against the actual object color and a reference color chart as introduced workflows in Figure 4. This quantitative evaluation method measures the visual discrepancies between the color values produced by the NeRF model and the precise color values noted on the reference chart, along with the true color observed in the object's natural environment. This is the formula for calculating CIEDE2000:

$$\Delta E^*_{00} = \sqrt{\left(\frac{\Delta L'}{k_L S_L}\right)^2 + \left(\frac{\Delta C'}{k_C S_C}\right)^2 + \left(\frac{\Delta H'}{k_H S_H}\right)^2 + R_T \frac{\Delta C'}{k_C S_C}\frac{\Delta H'}{k_H S_H}} \qquad (2)$$

$$\Delta L' = L^*_2 - L^*_1$$

$$\bar{L} = \frac{L^*_1 + L^*_2}{2} \quad \bar{C} = \frac{C^*_1 + C^*_2}{2}$$

$$a'_1 = a^*_1 + \frac{a^*_1}{2}\left(1 - \sqrt{\frac{\bar{C}^7}{\bar{C}^7 + 25^7}}\right) \quad a'_2 = a^*_2 + \frac{a^*_2}{2}\left(1 - \sqrt{\frac{\bar{C}^7}{\bar{C}^7 + 25^7}}\right)$$

$$\bar{C}' = \frac{C'_1 + C'_2}{2} \text{ and } \Delta C' = C'_2 - C'_1 \quad \text{where } C'_1 = \sqrt{a'^2_1 + b^{*2}_1} \quad C'_2 = \sqrt{a'^2_2 + b^{*2}_2}$$

$$h'_1 = \text{atan2}(b^*_1, a'_1) \mod 360°, \quad h'_2 = \text{atan2}(b^*_2, a'_2) \mod 360°$$

$$\Delta h' = \begin{cases} h'_2 - h'_1 & |h'_1 - h'_2| \leq 180° \\ h'_2 - h'_1 + 360° & |h'_1 - h'_2| > 180°, h'_2 \leq h'_1 \\ h'_2 - h'_1 - 360° & |h'_1 - h'_2| > 180°, h'_2 > h'_1 \end{cases}$$

$$\Delta H' = 2\sqrt{C'_1 C'_2}\sin(\Delta h'/2), \quad \bar{H}' = \begin{cases} (h'_1 + h'_2 + 360°)/2 & |h'_1 - h'_2| > 180° \\ (h'_1 + h'_2)/2 & |h'_1 - h'_2| \leq 180° \end{cases}$$

$$T = 1 - 0.17\cos(\bar{H}' - 30°) + 0.24\cos(2\bar{H}') + 0.32\cos(3\bar{H}' + 6°) - 0.20\cos(4\bar{H}' - 63°)$$

$$S_L = 1 + \frac{0.015\left(\bar{L} - 50\right)^2}{\sqrt{20 + \left(\bar{L} - 50\right)^2}} \quad S_C = 1 + 0.045\bar{C}' \quad S_H = 1 + 0.015\bar{C}'T$$

$$R_T = -2\sqrt{\frac{\bar{C}'^7}{\bar{C}'^7 + 25^7}}\sin\left[60° \cdot \exp\left(-\left[\frac{\bar{H}' - 275°}{25°}\right]^2\right)\right]$$

RESULTS

The results of the study comprehensively demonstrate the impact of camera profiling on color accuracy in Neural Radiance Fields (NeRF).

3.1 Colorimetric Analysis Outcomes

The colorimetric analysis, focusing on the Delta E metric, highlighted a marked improvement in color accuracy in images rendered from profiled cameras as shown in the results in Table 2. This was consistent across various scenes and under different lighting conditions. The analysis revealed that images from cameras with calibrated profiles closely matched the original scenes' colors, evidenced by significantly lower Delta E values. This part of the study emphasized the critical role of camera profiling in enhancing color accuracy in NeRF-rendered images, making it a pivotal aspect in achieving realistic digital representations.

Table 2: Color accuracy before and after profiling image dataset

Cameras	Without Profile		With Profile	
	ΔE*00 Mean	ΔE*00 Max	ΔE*00 Mean	ΔE*00 Max
LX100 mk2	3.67	8.11	2.79	6.78
iPhone12Pro	3.81	8.21	2.87	6.54
LG V40	4.13	9.32	2.98	6.84

The table shows the color accuracy for images taken by different cameras, both before and after the application of color profiling. Color accuracy is measured by Delta E (ΔE*00), where lower values indicate less deviation from the true color, hence better accuracy. The mean and maximum Delta E values are given for each scenario.

From this data, we can conclude that color profiling generally improves the color accuracy of images from different cameras, as evidenced by the reduction in both the mean and maximum ΔE*00 values. This improvement is consistent across different camera types, suggesting that color profiling is a robust method for enhancing color fidelity in digital imaging.

3.2 Comparison Across Different Camera Profiles

In analyzing the results of different camera profiles, the study found varying degrees of improvement in color accuracy. In general, the more sophisticated the camera profiling technique, the better the color fidelity of the NeRF render. This difference in results highlights the importance of the quality and precision of the camera profiling in achieving optimal color accuracy as shown at Figure 5. Table 3 shows how optimization of the profile leads to significant changes in the color difference. The quality of the profile optimization was evaluated by dividing it into matrix optimization, LUT optimization, and optimization for both matrix and LUT. The comparison between the different profiles provides a nuanced understanding of how the unique characteristics of each camera and its calibration procedure contribute to the overall color rendering effectiveness of NeRF. These insights are essential for developing more sophisticated camera profiling strategies in future digital rendering applications.

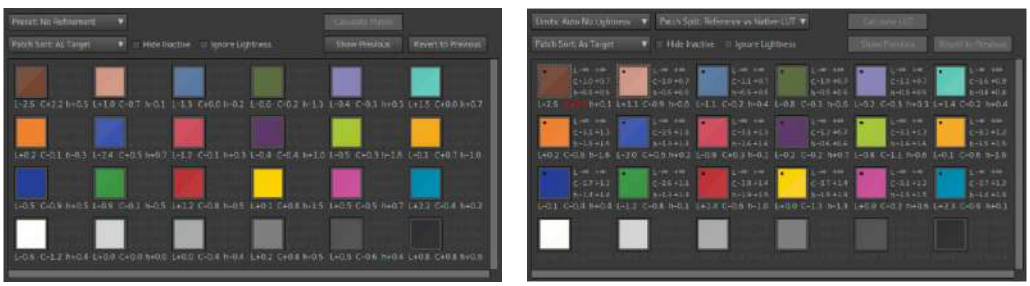

Figure 5: Matrix Optimizaiton and LUT Optimization process

Table 3: Differences in color quality of the NeRF due to profile optimization

Optimization	ΔE*00 Mean	ΔE*00 Max
Before optimization	2.79	6.78
Matrix tuned	2.68	4.32
LUT tuned	2.47	3.89
Matrix + LUT (ours)	2.41	3.74

Table 3 presents data comparing the color quality of a Neural Radiance Field (NeRF) before and after optimization using different color profiling methods, as indicated by the Delta E (ΔE*00) values. Delta E is a metric for understanding how the human eye perceives color difference; the lower the value, the less perceivable the color difference is.

The initial state of the NeRF has a mean ΔE*00 of 2.79 and a maximum ΔE*00 of 6.78. These values suggest that before any optimization, there was a noticeable color discrepancy from the target or reference color that could likely be detected by the human eye.

After applying a matrix-based optimization, which typically involves adjusting the color balance and cross-channel color mixing, the mean ΔE*00 is slightly reduced to 2.68, and the maximum ΔE*00 is significantly lowered to 4.32. This indicates an improvement in the overall color accuracy, with the most noticeable discrepancies being reduced.

Generally, LUT (Look-Up Table) tuning refers to a more granular color adjustment that can correct specific ranges or hues within an image.

Combining both matrix and LUT optimizations results in the best color accuracy, with a mean ΔE*00 of 2.41 and a maximum of 3.74. This suggests that using both methods together is most effective at reducing color differences in the NeRF rendering.

Overall, the optimizations applied to the NeRF have led to improvements in color accuracy, with the combination of matrix tuning and LUT tuning providing the best results. This is likely due to the comprehensive approach in adjusting both the overall color balance and the specific hues, leading to a closer match to the desired color representation.

3.3 Analysis of Rendered Images under Various Conditions

The study also delved into how camera profiling influenced color accuracy under a range of lighting conditions. It was found that camera profiling significantly contributed to maintaining color consistency and accuracy across these varying scenarios. This aspect was particularly prominent in scenes with complex lighting, where challenges in color rendition are usually more pronounced. The analysis shows that camera profiling is not just beneficial under controlled conditions but is also crucial in diverse and dynamic real-world rendering situations.

Table 4 shows how the color of the color checker chart changes as a result of simulating a scene with different light sources.

Table 4: Simulate Scenes with Different Light Types

Light Sources	SDR	HDR
Direct Light		
Diffused Light		
Backlight		

Table 5: Differences in color accuracy for different scenes

Scene	SDR		HDR	
	ΔE*00 Mean	ΔE*00 Max	ΔE*00 Mean	ΔE*00 Max

Direct light	4.89	9.31	3.42	5.81
Diffused Light	3.21	7.21	2.98	6.87
Backlight	5.32	10.24	3.79	8.97

Table 5 compares the color accuracy of images captured in different lighting scenes, analyzed under standard dynamic range (SDR) and high dynamic range (HDR) conditions. Color accuracy is measured using Delta E (ΔE^*00), with both mean and maximum values reported for each scene and dynamic range setting.

In scenes with direct light, the color accuracy is lower compared to other lighting conditions, as evidenced by higher ΔE^*00 values. This suggests that direct light poses a challenge for accurate color reproduction. However, when HDR is applied, there is a notable improvement in color accuracy. The mean Delta E decreases, and the maximum Delta E value sees a significant reduction, indicating that HDR helps mitigate the color inaccuracies caused by the harshness of direct lighting.

For scenes under diffused light, which typically presents a more uniform lighting condition, the color accuracy is inherently better than in direct light scenarios, as shown by the lower mean and maximum Delta E values. This higher color accuracy is further improved by HDR, suggesting that while SDR performs reasonably well under diffused light, HDR can enhance color fidelity even further.

Backlit scenes, which are challenging due to the contrast between light and shadow, show the highest Delta E values under SDR, indicating the poorest color accuracy among the listed conditions. However, the application of HDR reduces these values considerably, though not as dramatically as in direct lighting. This suggests that while HDR can significantly improve color reproduction in backlit scenes, these conditions still present a substantial challenge to achieving color accuracy.

Overall, the data indicates that HDR consistently improves color accuracy across different lighting scenes, reducing both the mean and maximum Delta E values when compared to SDR. This improvement is most pronounced in direct light conditions, emphasizing the effectiveness of HDR in handling extreme lighting contrasts to enhance color fidelity.

3.4 Evaluation of NeRF Configuration Efficacy

The effectiveness of the Neural Radiance Fields (NeRF) configuration in the study is examined with a specific focus on how well it adapts to varied camera profiles. The NeRF system's ability to render images that align closely with the original scenes' colors suggests a high degree of configurational efficacy. This implies that the system's algorithms were successfully fine-tuned to interpret and apply the unique color information inherent to each camera's profile. Such an outcome not only demonstrates the NeRF's flexibility but also its capacity to incorporate detailed color calibration data, which is vital for applications where color precision is critical.

This adaptability is particularly relevant in fields such as digital art restoration, where the exact hues of original works must be preserved, or in product visualization, where accurate color representation can influence consumer perception and decision-making. The NeRF's capability to effectively translate the camera profiles into visually accurate renderings suggests that it can serve as a reliable tool in these and other domains, potentially aiding in tasks that require a high level of color consistency, such as in the creation of digital twins for virtual prototyping or in simulation-based training environments where visual cues are crucial.

Moreover, this adaptability bodes well for the future integration of NeRFs with other imaging technologies. For example, in medical imaging, where precise color rendition can aid in diagnosis, the ability of NeRFs to accurately render colors as they would appear to the human eye or in other imaging modalities could be of significant benefit. In cultural heritage, where the authentic representation of artifacts is essential, NeRFs could assist in creating digital archives that faithfully reproduce the original colors, even under varying viewing conditions.

The study's evaluation of NeRF configuration efficacy thus highlights the technology's potential to become a standard tool in industries where color accuracy is not a mere aesthetic preference but a functional necessity. As NeRF continues to evolve, further research could explore its integration with dynamic lighting environments and real-time color correction, pushing the boundaries of how we interact with and interpret the colors of digital objects. Figure 6 shows the resulting difference in image color between no color adjustment and color management for NeRF.

Non Color managed	**Color managed for NeRF**

Figure 6: Without color adjustment and with color management for NeRF

DISCUSSION

The study's findings, pivoting around the critical role of camera profiling in enhancing color accuracy in NeRFs, prompt a nuanced discussion on the implications, challenges, and future directions of this integration. The remarkable improvements in color fidelity, evidenced by the lowered Delta E values across various cameras and scenes, underscore the potential of camera profiling to achieve photorealistic digital imagery.

The improvements in color accuracy are significant, given the challenging nature of replicating true-to-life colors in digital renderings. This success is particularly noteworthy in the context of diverse lighting conditions, where HDR processing notably outperformed SDR. The reduction in color discrepancies under direct, diffused, and backlight conditions when using HDR demonstrates its robustness in enhancing the visual quality of NeRF-generated images.

However, the integration of camera profiling is not without its challenges. The complexity introduced into the NeRF rendering process by camera profiling necessitates a careful balance between color accuracy and computational efficiency. Future developments must address this by optimizing algorithmic processes to accommodate the added computational load without compromising rendering speed or scalability.

Looking ahead, the integration of camera profiling with emerging technologies such as artificial intelligence and machine learning presents a fertile ground for innovation. These technologies could potentially automate and refine the profiling process, making NeRFs more adaptive and responsive to real-time changes in lighting and color conditions. This could broaden the application of NeRFs in areas requiring dynamic color accuracy, such as augmented reality, remote sensing, and autonomous navigation systems.

The study's exploration of camera profiling's impact also extends to user experience. As the perceptual analysis revealed, the quality of digital imagery significantly affects user engagement and satisfaction. By enhancing color fidelity, NeRFs could provide more immersive experiences in virtual reality and gaming, enabling users to feel a deeper connection to the digital world.

In summary, this investigation into camera profiling's role in color management within NeRFs not only demonstrates its efficacy but also opens up several avenues for future research. The pursuit of a more refined, efficient, and user-centered approach to digital rendering continues, with the promise of making photorealistic digital imagery more accessible and versatile across various domains.

CONCLUSION

This study has explored the multifaceted approach of incorporating camera profiling into NeRFs, highlighting a significant enhancement in the realm of digital color accuracy. The methodical selection and profiling of cameras, the meticulous scene composition, and the tailored NeRF configuration culminated in a robust evaluation of color fidelity, revealing tangible improvements across various cameras and lighting conditions.

The quantitative leap in colorimetric performance, marked by the substantial decrease in ΔE^*00 values, underscores the effectiveness of camera profiling. This advancement is not only a testament to the proficiency of the profiling techniques but also to the adaptability of NeRFs to diverse lighting conditions, particularly benefiting from HDR's capacity to mitigate the variances in challenging lighting environments like direct light and backlight.

These technical achievements, however, bring to light the intricate balance between color accuracy and computational demands. The profiling process, while essential for color precision, adds a layer of complexity that requires careful consideration in computational resource management. The future trajectory of this field lies in refining these processes, potentially harnessing the power of emerging technologies to streamline and automate profiling, thus alleviating computational burdens.

The practical implications of this study are far-reaching. Enhanced NeRF models, equipped with camera profiling, have the potential to revolutionize industries that rely heavily on color accuracy, from content creation in virtual reality to precision-required tasks in medical imaging. Additionally, the improved color fidelity has a profound impact on user experience, offering a more immersive and realistic interaction with digital content.

In envisioning the future, the field stands on the cusp of integrating NeRFs with advanced machine learning and artificial intelligence algorithms, a synergy that promises to deliver real-time adaptability and further advancements in digital imaging. The journey towards achieving photorealistic digital representation continues, with the learnings from this study serving as a cornerstone for future innovations.

This paper's comprehensive examination of camera profiling's impact on NeRFs contributes significantly to the advancement of digital imagery, bridging the gap between digital representations and real-world color perception. It opens the door for future research to explore new dimensions in digital rendering, with the goal of achieving an unparalleled level of color accuracy in computer graphics and beyond.

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REFERENCES

[1] Mildenhall, B.; Srinivasan, P.P.; Tancik, M.; Barron, J.T.; Ramamoorthi, R.; Ng, R. NERF: Representing Scenes as Neural Ra-diance Fields for View Synthesis. arXiv (Cornell University) 2020, doi:10.48550/arxiv.2003.08934.

[2] Morganai, J. Understanding NERF: Neural Radiance Fields Available online: https://www.fablabconnect.com/understanding-nerf-neural-radiance-fields/.

[3] Neural Radiance Field (NERF): A Gentle Introduction Available online: https://datagen.tech/guides/synthetic-data/neural-radiance-field-nerf/.

[4] Xie, Y.; Takikawa, T.; Saito, S.; Litany, O.; Yan, S.; Khan, N.; Tombari, F.; Tompkin, J.; Sitzmann, V.; Sridhar, S. Neural Fields in Visual Computing and Beyond. Computer Graphics Forum 2022, 41, 641–676, doi:10.1111/cgf.14505.

[5] Dey, A.; Comport, A.I. RGB-D Neural Radiance Fields: Local Sampling for Faster Training. HAL (Le Centre Pour La Commu-nication Scientifique Directe) 2022.

[6] Lazova, V.; Guzov, V.; Olszewski, K.; Tulyakov, S.; Pons-Moll, G. Control-NERF: Editable Feature Volumes for Scene Ren-dering and Manipulation. 2023 IEEE/CVF Winter Conference on Applications of Computer Vision (WACV) 2023, doi:10.1109/wacv56688.2023.00432.

[7] Yan, Z.; Li, C.; Lee, G.H. NERF-DS: Neural Radiance Fields for Dynamic Specular Objects. arXiv (Cornell University) 2023, doi:10.48550/arxiv.2303.14435.

[8] Penczek, J.; Boynton, P.A.; Splett, J.D. Color Error in the Digital Camera Image Capture Process. Journal of Digital Imaging 2013, 27, 182–191, doi:10.1007/s10278-013-9644-1.

[9] Cahyadi, W.A.; Chung, Y.H.; Ghassemlooy, Z.; Hassan, N.B. Optical Camera Communications: Principles, Modulations, Po-tential and Challenges. Electronics 2020, 9, 1339, doi:10.3390/electronics9091339.

[10] Fisher, A.; Cannizzaro, R.; Cochrane, M.; Nagahawatte, C.; Palmer, J.L. ColMap: A Memory-Efficient Occupancy Grid Map-ping Framework. Robotics and Autonomous Systems 2021, 142, 103755, doi:10.1016/j.robot.2021.103755.

[11] Tancik, M.; Weber, E.; Ng, E.; Li, R.; Yi, B.; Kerr, J.; Wang, T.; Kristoffersen, A.; Austin, J.; Salahi, K.; et al. NerfStudio: A Mod-ular Framework for Neural Radiance Field Development. arXiv (Cornell University) 2023, doi:10.48550/arxiv.2302.04264.

[12] Zhang, K.; Riegler, G.R.; Snavely, N.; Koltun, V. NERF++: Analyzing and Improving Neural Radiance Fields. arXiv (Cornell University) 2020.

[13] Sharma, G.; Wu, W.; Dalal, E.N. The CIEDE2000 Color-Difference Formula: Implementation Notes, Supplementary Test Data, and Mathematical Observations. Color Research and Application 2004, 30, 21–30, doi:10.1002/col.20070.

[14] Tewari, A.; Fried, O.; Thies, J.; Sitzmann, V.; Lombardi, S.; Sunkavalli, K.; Martin-Brualla, R.; Simon, T.; Saragih, J.; Nießner, M.; et al. State of the Art on Neural Rendering. arXiv (Cornell University) 2020.