Alpha-rooting Color Image Enhancement for Neural Light Field Rendering

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ABSTRACT

In this paper, we explore the use of low-light image enhancement as a preprocessing step to improve the quality of novel view synthesis by Neural Light Fields (NeLF). NeLF is a 3D scene representation method that employs a light field representation, which differs from prior methods based on volumetric rendering schemes. One of the main advantages of NeLF is its faster rendering speed, as it requires only one network forward pass without Ray marching. However, NeLF struggles to model low-illumination scenes due to its viewer-centered framework, which does not consider the interaction between illumination and scenes. To address this issue, we propose the use of 2D low-light image enhancement as a preprocessing solution. Our approach utilizes the Alpha rooting by 2-D DFT as a preprocessing step to enhance low-light images before feeding them to the NeLF model. We demonstrate that this approach leads to significant improvements in the quality of novel view synthesis by NeLF on low-light images. We also show this can have practical applications in various domains such as applied Human biomechanics.

Keywords: Alpha rooting, low light image enhancement, discrete Fourier transform, View synthesis

1. INTRODUCTION

Low light image enhancement has been an active research area due to its applications in various domains [1-7]. In recent years, various methods have been proposed to improve the visual quality of low-light images. However, most of these methods are machine learning-based techniques, which require large amounts of data and computational resources. Most of these current techniques have been effective at low light image enhancement, as they are deep learning-based methods trained on a curated dataset, and thus are also susceptible to adversarial attacks in this regard [4-7]. In contrast to these state-of-the-art deep learning-based techniques for low-light image enhancement, we propose a traditional Fourier transform-based method that achieves satisfactory results while avoiding some of the drawbacks and limitations of the learning-based approach to image enhancement [8-14]. Additionally, we demonstrate our method has promising applications in human pose estimation and biomechanics using computer vision and graphics[15-19]. This is based on its benefit to neural light field rendering for view synthesis from low-light images/videos [20-21].

View synthesis by Neural light fields (NeLF) is an emerging technique for improving 3D scene representation [22-28]. However, the deployment of vanilla neural light fields in the wild fails to model low-illumination-induced darkness since they are not trained on low-light images [7]. Therefore, there is a need to enhance the quality of low-light images before using them for NeLF applications. This paper analyzes the application of the alpha-rooting method by the two-side two-dimensional discrete Fourier transform (2-D DFT) followed by a spatial transformation to achieve Low Light Image Enhancement (LLIE). The proposed method represents color images in the frequency domain, which enables the representation of each of the three-color components of an sRGB image as a composition of frequencies [11-14]. This proposed method improves the visual quality of low-light images by enhancing their color brightness and contrast detail, which is essential for improving the quality of neural light field rendering to increase their effectiveness at novel view synthesis based on low-light images.

The proposed alpha-rooting method is a traditional Fourier transform-based image enhancement technique that has been effectively used on both grayscale and color images when processed channel-by-channel [14]. This method has also been largely overlooked in recent comparisons and surveys of low-light image enhancement techniques [1-4]. This is why we emphasize the efficacy of the Alpha-rooting by 2-D DFT method as a promising alternative to deep learning-based methods for low-light image enhancement. By highlighting the computational efficiency and easy implementation of our method compared to state-of-the-art techniques, we hope to draw more attention to it and encourage further research in this area. More so, by enhancing the brightness and contrast of low-light images, the proposed alpha-rooting method is effective as a pre-processing step for improving the multi-view consistency of the NeLF. This allows more useful features to be extracted and effectively learned from the enhanced images [26-28]. This hybrid approach can potentially open up new avenues for research in the field of computer vision and graphics.

In the field of computer vision and graphics, human motion analysis is a domain that can potentially benefit from our proposed technique. The benefits include enabling more realistic and immersive virtual avatars and environments for human motion assessment, especially accurate analysis of human poses from a single frame [15-17]. Further enhancement to the visual quality of low-light images can improve the accuracy of neural light field rendering for novel view synthesis of human poses. The ability to generate high-quality novel views of human poses from a single image or video sequence has numerous applications in Tele healthcare, Fitness/wellness, gaming, and cinematography [18-19]. For example, in biomechanics research and physical therapy, human movements could be captured in low illumination conditions for gait analysis. Then, the enhanced images produced by our proposed method could improve the accuracy of these analyses. Similarly, in fitness performance tracking, low-light imaging could be used to capture exercise sessions and the enhanced images could provide clearer visualizations of movement and form.

2. IMAGE ENHANCEMENT

2.1. Light field imaging

First introduced by Adelson and Bergen in 1991 [20], light field imaging is a technique that captures both the intensity and direction of light rays from a scene, enabling novel view synthesis from a captured set of images. Light field images consist of multiple views of a scene, resulting in a high-dimensional data structure that requires significant computational resources for processing and analysis [21]. One of the key challenges in light field imaging is dealing with the large amount of data generated. Several methods have been proposed for processing and analyzing light field data, including image-based rendering techniques and deep learning approaches such as Neural rendering [21-28]. However Low illumination still poses a unique challenge for many light field imaging applications.

Low light conditions can significantly affect the quality of light field images, making it more difficult to generate realistic novel views based on Neural Light Field. Surprisingly, there have been no specific studies that address the enhancement of Low light images from Light field datasets to improve Neural Light Field rendering. However, there is a concurrent study that addresses the adjacent challenge of enhancing Low light Images for Neural Radiance Fields [7]. The concurrent study proposes an unsupervised learning-based approach for addressing image enhancement to improve the quality of novel views generated from Neural radiance fields. In contrast, our technique of Alpha-Rooting by the 2-D DFT is a traditional Fourier Transform-based method.

2.2. Low Light Image Enhancement

The essential task of Low light image enhancement is applicable in a variety of fields, including computer vision, medical imaging, remote sensing, and texture analysis [3-6]. Low-light images often suffer from poor quality and low contrast, making it challenging to use them for novel view synthesis applications. Low-light images are typically enhanced when considered as color images in the sRGB space [8]. Traditional and modern learning-based techniques show that color images can only be effectively processed if the color of the image is considered as the sum of the color component pixel values in all channels when taken together [1-14].

The use of color components summation provides a good baseline for our proposed alpha-rooting method to be evaluated on both single-view and multi-view paired low-light and normal-light image datasets. We use the single view LIME and LOL datasets to test the Alpha rooting and compare it with both the LIME and RetinexNet deep learning-based techniques [1, 2]. Then we use a multi-view LOM dataset to test the effects of the Low light enhancement on the Neural Light Field (NeLF) results, and also compare it with the Ground truth image and the baseline NeLF [7]. Image enhancement measures will be used to show our proposed method achieves satisfactory contrast and color preservation, leading to a significant improvement in the quality of the enhanced images [9, 12].

3. ALPHA ROOTING COLOR IMAGE ENHANCEMENT

3.1. Alpha Rooting 2D-DFT

Alpha rooting is a traditional image enhancement technique that processes images in the frequency domain, by using the discrete Fourier transform (DFT). The alpha-rooting in the frequency domain can be described by the Taylor series, as well as in the spatial domain, by using the inverse 2-D DFT [13]. In such a series, the alpha-rooting is the convolution of the image with the series of autocorrelation functions. The α-rooting method can be considered an optimization problem where the objective is to find the best parameter α which maximizes the CEME function. Thus, some optimization solutions have been proposed to meet this objective [12, 13]. Also, the enhancement of images in the quaternion space has been proposed for improving color images by treating all three-color channels as one [14].

In the alpha-rooting method of image enhancement by 2-D DFT of an image $\{f_{n,m}\}$ of size $N \times M$ pixels, the magnitude of the transform at each frequency-point (p,s) is transformed as

$$F_{p,s} \rightarrow M_\alpha[F_{p,s}], \text{ i.e., } |F_{p,s}| \rightarrow [F_{p,s}]^\alpha, \quad p = 0:(N-1), s = 0:(M-1),$$

Here, α is from the range of [0,1]. Thus, Alpha-rooting consists of only a few key operations:

1) Take the 2D DFT of the input image:

$$F_{p,s} = \text{2D-DFT } [\, f_{n,m}].$$

2) Transform the magnitude of the 2D DFT by applying a parameterized exponent $(\alpha - 1)$:

$$A(p,s) = |F_{p,s}|^{\alpha-1}.$$

3) Multiply the original 2D DFT by the coefficients of the transformed magnitude matrix: $Y_{p,s} = F_{p,s}A(p,s)$.

4) Take the inverse 2D DFT of this resultant matrix to obtain the final output image:

$$y_{n,m} = \frac{1}{N \cdot M} \sum_{p=0}^{N-1} \left[\sum_{s=0}^{M-1} Y_{p,s} W_M^{-ms} \right] W_N^{-pn}, \quad n = 0:(N-1), m = 0:(M-1).$$

The alpha root of the transformed frequency values of the 2-D DFT is determined before taking the inverse transform. The optimal value of alpha (α) is determined by selecting the value in the range of [0,1] that gives the maximum enhancement measure value. The enhancement measure values are calculated using the color enhancement measure estimation (CEME) and Power to Signal Noise Ratio (PSNR), which are based on the visual perception and the signal procession of the reference sRGB image. Also, since the 2D-DFT approach of color image enhancement allows the representation of each sRGB color in the frequency domain, we are able to quantify and see the merging effect of the image color due to the holistic combination of the primary colors.

3.2. Enhanced Image Quality Metrics

The first image quality metric used is the color enhancement measure estimation (CEME) [11,14]. The CEME is an enhancement measure used to determine the quality of enhancement based on the contrast between the original and enhanced images. This measure is the analog of the EME measure for grayscale images [9],[11]. The CEME is linked to the Weber law, which states that the human visual system's ability to detect contrast is not affected by changes in luminance or low spatial frequency. The CEME is specifically used to find the best parameters for the alpha value. The CEME is calculated by dividing a discrete image $\{f_{n,m}\}$ of size $N \times M$ pixels by $k_1 k_2$ blocks of size $L_1 \times L_2$ pixels each, where $k_n = [N_n/L_n]$. Then, the average of the range of intensity of all blocks is calculated on a logarithmic scale. The EMEC is defined by

$$E(\alpha) \ = \ CEME(f) = \frac{1}{k_1 k_2} \sum_{k=1}^{k_1} \sum_{l=1}^{k_2} 20\log_{10} \left[\frac{\max_{k,l}(f_R, f_G, f_B, f_I)}{\min_{k,l}(f_R, f_G, f_B, f_I)} \right].$$

In this context, k_1 and k_2 specify the total number of complete blocks present in the image. Additionally, the terms $max_{k,l}(f_R, f_G, f_B)$ and $min_{k,l}(f_R, f_G, f_B)$ indicate the maximum and minimum values of the color image $f_{n,m}$ inside the (k, l)-th block, respectively. Essentially, the image is subdivided into $k_1 \times k_2$ blocks, each of size $L \times L$ pixels, for instance 7×7. For each block, the ratio between the maximum and minimum pixel value among all channels is taken in the logarithmic scale and summed with the rest of the blocks. The gray or intensity value f_I can also be considered. This sum is finally normalized by the number of blocks into which the color image was subdivided. Note that here the color image need not be made up of 3 channels, rather the image can have some arbitrary positive integer number of channels.

The other relevant image quality metric used is the peak signal-to-noise ratio (PSNR). The PSNR measures the quality difference between an original and an enhanced one based on the peak signal-to-noise ratio in decibels [8]. A higher PSNR value usually indicates better quality in the enhanced image. For color images, the signal $s(f)$ of each channel is effectively computed and the average of these is taken to obtain the PSNR of the overall color image. The PSNR for a single channel is computed as follows:

$$\text{mean[PSNR]} = 20log_{10}\left[\frac{225}{s(f)}\right],$$

where $s(f)$ is computed as

$$s(f) = \frac{1}{NM} \sum_{n=0}^{N-1} \sum_{m=0}^{M-1} f_{n,m} - mean[f]^2$$

Then, for a color image based on the sRGB model, the PSNR is computed as follows;

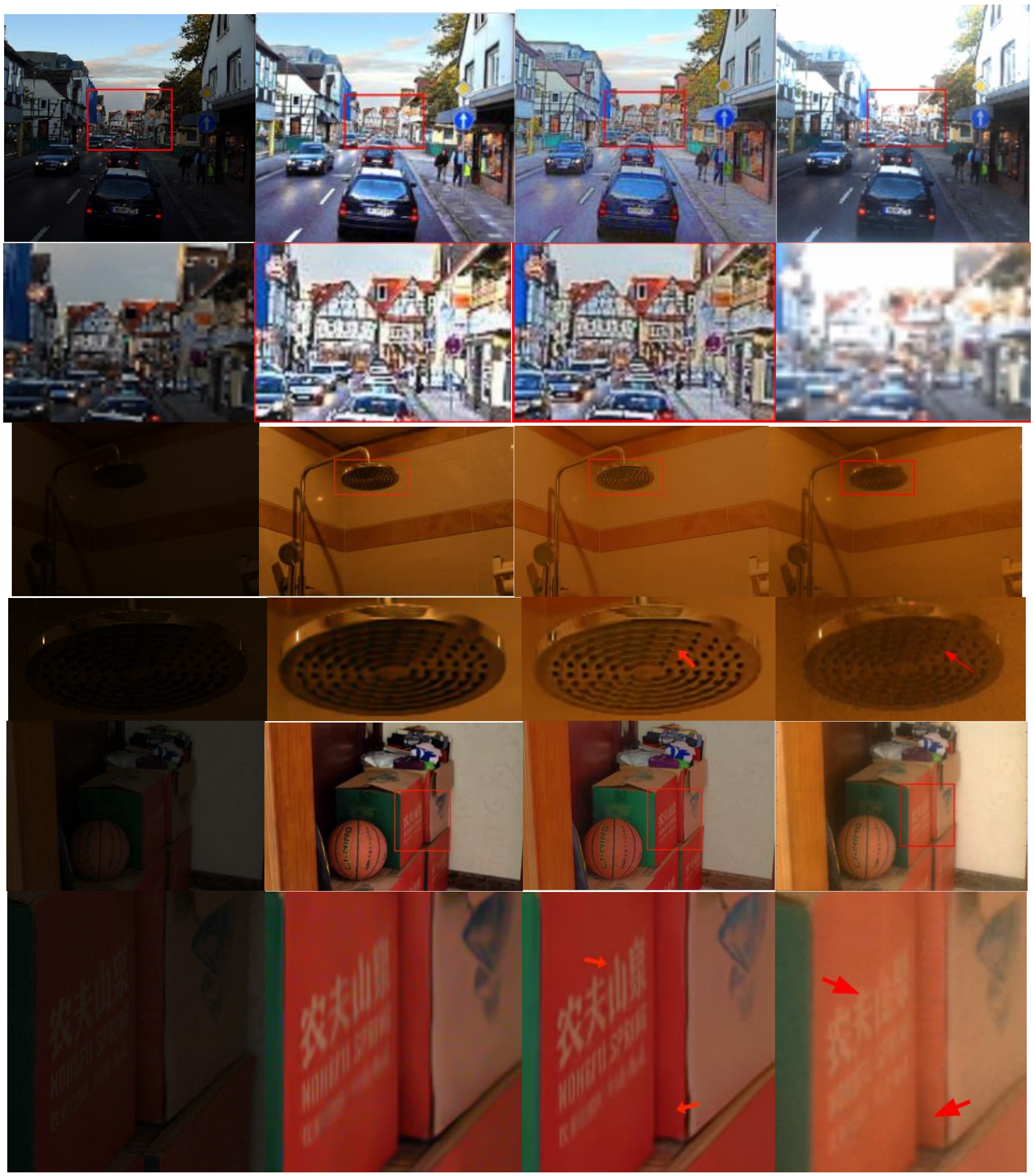
$$\text{mean [PSNR]} = 20log_{10}\left[\frac{225}{\frac{1}{3}(s_R(f) + s_G(f) + s_B(f))}\right],$$

where, for each color K=R,G, and B, the component $s_K(f)$ is computed as

$$s_K(f) = \frac{1}{NM} \sum_{n=0}^{N-1} \sum_{m=0}^{M-1} k_{n,m} - mean[k]^2.$$

3.3. Single View Low Light Image Enhancement

In this section, we first test the Alpha rooting by 2-D DFT on the Single view LIME and LOL datasets [1, 2]. This is to provide a comparative placement of our method among contemporary deep learning-based low-light Image enhancement methods [3-6]. The qualitative comparison with the LIME and the RetinexNet deep learning methods is shown in Fig. 1. Both datasets combined, consists of 500+ paired low-light images and normal-light images, all resized to 400×600. It provides 485 images for training and 15 for testing. Each image pair in the dataset consists of a low-light input image and its corresponding well-exposed reference image. We report the CEME↑ and PSNR↑ image quality metrics using the quantitative comparison in Table 1. Overall, our method gains satisfactory results, ensuring the enhanced images are high-quality and vivid compared with the other enhancement methods.



(a) Low Light (b) LIME (c) RetinexNet (d) Alpha-rooting

Figure 1. Single-view enhancement results (top to bottom) on **LIME** dataset's "***street***", and **LOL** dataset's "***showerhead***", and "***carton***" scenes.

Low Light Image Enhancement Method	street		showerhead		carton	
	CEME	PSNR	CEME	PSNR	CEME	PSNR
LIME	20.41	14.78	17.71	12.55	14.77	12.21
RetinexNet	21.23	12.66	22.78	11.87	14.56	12.55
Alpha-rooting (Ours)	18.47	12.23	21.44	11.45	16.72	10.35

Table 1. CEME↑ and PSNR↑ results on the **LIME** and **LOL** dataset's scenes.

4. ALPHA ROOTING ENHANCED NOVEL VIEW SYNTHESIS

4.1. Neural 3D Scene Representation

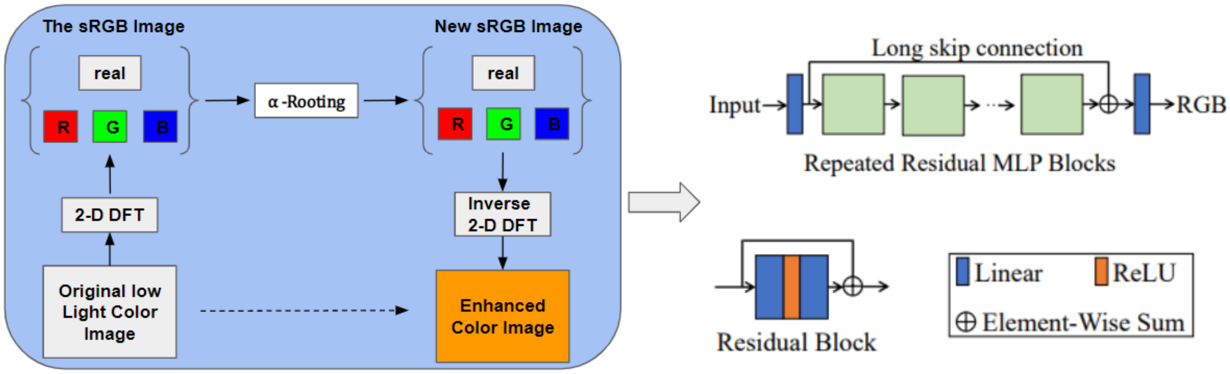
Neural rendering is a 3D Scene Representation method that uses a neural network to synthesize new views of a scene from a collection of input images during both training and inference [22-28]. This involves using a neural network to represent the shape and appearance of the scene. While there are various methods for 3D scene representation such as Image Based Rendering and Neural Radiance Field, NeLF stands out because it uses a light field representation instead of volumetric rendering [24-28]. NeLF is also faster than NeRF since rendering one image only requires one network forward pass without Ray marching. In this section, we introduce the R2L NeLF Network [28], which will be used for rendering novel views from a set of input images.

R2L is a NeLF function that uses a new ray representation by sampling points along the ray and concatenating them to a vector fed into a neural network for learning RGB [28]. It adopts positional encoding and uses an 88-layer deep ResMLP (residual MLP) architecture to improve the NeLF representation learning. R2L has two stages of training, using a pre-trained NeRF teacher model to synthesize pseudo data and then fine-tuning the network on the original data to improve rendering quality. R2L directly outputs RGB values without learning density or alpha-compositing, making it faster than NeRF in rendering. However, the NeLF representation is harder to learn than NeRF, which R2L addresses through its deep ResMLP architecture.

Low-light image enhancement is an essential preprocessing step since both vanilla and R2L NeLF are unsuitable for modeling scenes with low illumination. These algorithms are viewer-centered and do not account for the interaction between illumination and scenes [7]. This leads to poor reconstruction results when trained on dark images with high zero-mean noise. Maintaining multi-view projection consistency is challenging for NeLF algorithms, and solutions such as object-centered rendering introduce additional complexity in the overall model design. 2D low-light image enhancement is a suitable alternate solution, especially when the correlation between image channels is holistically considered in the enhancement process. Here, we apply our method as an effective preprocessing step for the NeLF.

4.2. General Scheme of the Alpha-rooting Proposed Method

A typical low-light color image comprises multiple monochromatic channels, each representing a specific color component [8]. More generally, all color images consist of 3 or 4 channels of monochromatic images. The color of the image is resolved to color components, and pixel values in each channel are the corresponding color image intensities. For example, in the RGB color model, the image is stored as three monochromatic images for the red, green, and blue colors. The original color in the image is the color obtained by superposing or merging all three-color components. We implement our low light image enhancement method by treating and operating on these color channels separately, as well as applying a global alpha-rooting value to all the channels.



(a) Detailed architecture of the Alpha rooting by 2D-DFT

(b) Detailed architecture of the R2L NeLF network from the source paper

Figure 2. Alpha-rooting enhanced **R2L** Neural Light Field Architecture.

Alpha-rooting by the 2-D DFT uses the sRGB color model to represent a color image in the frequency domain, then an optimal alpha value is used to transform the magnitude of the frequencies. After enhancement, the preprocessed image is fed into the R2L NeLF, which uses extensive repeated residual MLP blocks (Neural Networks) to render out the novel views of the new Scene by light field imaging-based 3D Scene representation. The use of a light field to represent a scene instead of a radiance field ensures that the output of the NeLF network is already the wanted color. This is contrasted with the output of a NeRF network whose output is the radiance of a sampled point, thus requiring the use of an extra step of ray marching to obtain the desired color of the images and scene.

4.3. R2L Teacher Light Field Parametrization

The R2L NeLF uses a pre-trained Neural radiance field (NeRF) model to synthesize extra data for training, as deep networks require excessive data to be powerful [28]. The use of Synthetic data is necessitated as less than 100 images of a scene are typically captured for novel view synthesis. Thus, the use of sparse dataset makes R2L NeLF compatible with our use of image preprocessing prior to the neural light field rendering stage. For a trained NeRF model, F_{Θ^*}, that uses volumetric rendering by randomly sampling along a ray origin (x_o, y_o, z_o) and normalized direction (x_d, y_d, z_d), the target RGB value can be queried as:

$$(\hat{r}, \hat{g}, \hat{b}) = F_{\Phi^*}(x_0, y_0, z_0, x_d, y_d, z_d).$$

Here, Θ^* represents the converged model parameters of the origins and normalized direction. Then a slice of the synthetic training data is simply a vector of these 9 numbers: $(x_o, y_o, z_o, x_d, y_d, z_d, \hat{r}, \hat{g}, \hat{b})$. To have an effective neural light field network F_Θ, abundant pseudo (i.e., synthetic) data is fed into the proposed deep R2L network and trained by the MSE loss function,

$$L = MSE\left(F_{\Phi}(x_0, y_0, z_0, x_d, y_d, z_d), (\hat{r}, \hat{g}, \hat{b})\right).$$

For the R2L training Stage, all model design considerations and parameters are faithfully followed based on the implementation from the original paper [28]. They used 6M and 12M FLOPs (per ray) to train the Model which results in a bunch of networks with varying widths and depths. We use the 12M FLOPs implementation, as it results in better quality renders from the training dataset.

5. EXPERIMENTAL RESULTS

5.1. Multi View Low Light Image Enhancement

We use the Multiview LOM dataset to test the effects of the Low light enhancement on the Neural Light Field results. The LOM dataset is the first paired low-light and normal-light Multi-view (LOM) dataset collected [7]. The dataset contains 5 real-world scenes (“buu”, “chair”, “sofa”, “bike”, “shrub”), captured with a professional action camera. There are 25 to 65 images for each scene with low-light and normal-light pairs. All images used from the dataset will be down sampled by ⅛ to 375 x 500 as directly cited from the reference paper. Then, comparison experiments are used to evaluate the image generation quality and multi-view consistency of both the baseline and Image enhanced R2L NeLF. We compare the Alpha-rooting enhanced (+) R2L NeLF with the baseline R2L NeLF, LIME enhanced (+) NeLF, RetinexNet Enhanced (+) NeLF, and the Ground truth image. The CEME and PSNR Image enhancement measures are used to show our proposed method achieves satisfactory contrast and color preservation compared to the deep learning-based methods, leading to a significant improvement in the quality of the enhanced images.

5.2. Qualitative and Quantitative Results

Using the real data alone, our Alpha-rooting + R2L NeLF achieves comparable performance to the original NeLF model on the ground truth image either quantitatively or qualitatively, without incurring any significant additional computational cost compared to the deep learning-based approaches.

To qualitatively measure the level of enhancement based on visual quality, we apply a scaling transformation to the enhanced image after alpha-rooting. This is to accommodate the human visual perception of the enhancement quality based on the level of perceived illumination. This is because the pre-scaled enhancement result does not provide enough illumination to visually illustrate the brightness and contrast achieved, due to intensity levels.

The Visual results in Fig. 7 show that our method delivers better visual quality than the baseline R2L NeLF, and achieves comparable quality to the LIME and RetinexNet methods. On the four scenes selected, our R2L network achieves better rendering quality than LIME and RetinexNet despite not using a learning-based approach.

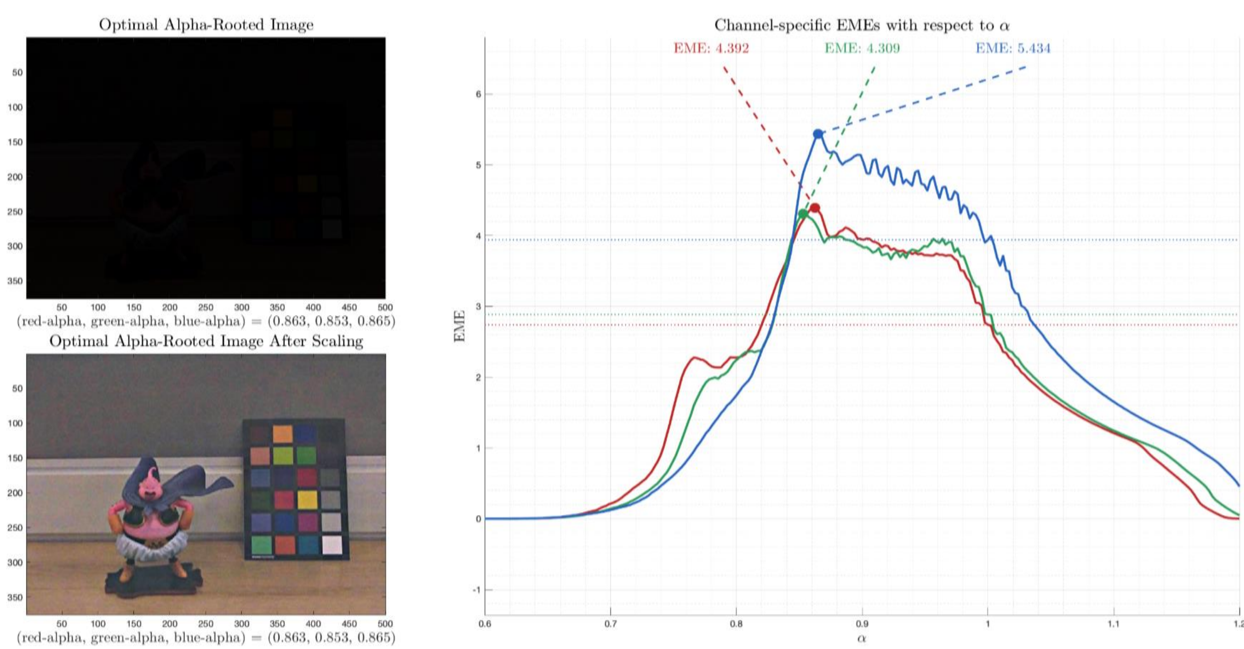


Figure 3. RGB Alpha-rooting results in the front-facing view of the **LOM** dataset’s “**buu**” scene.

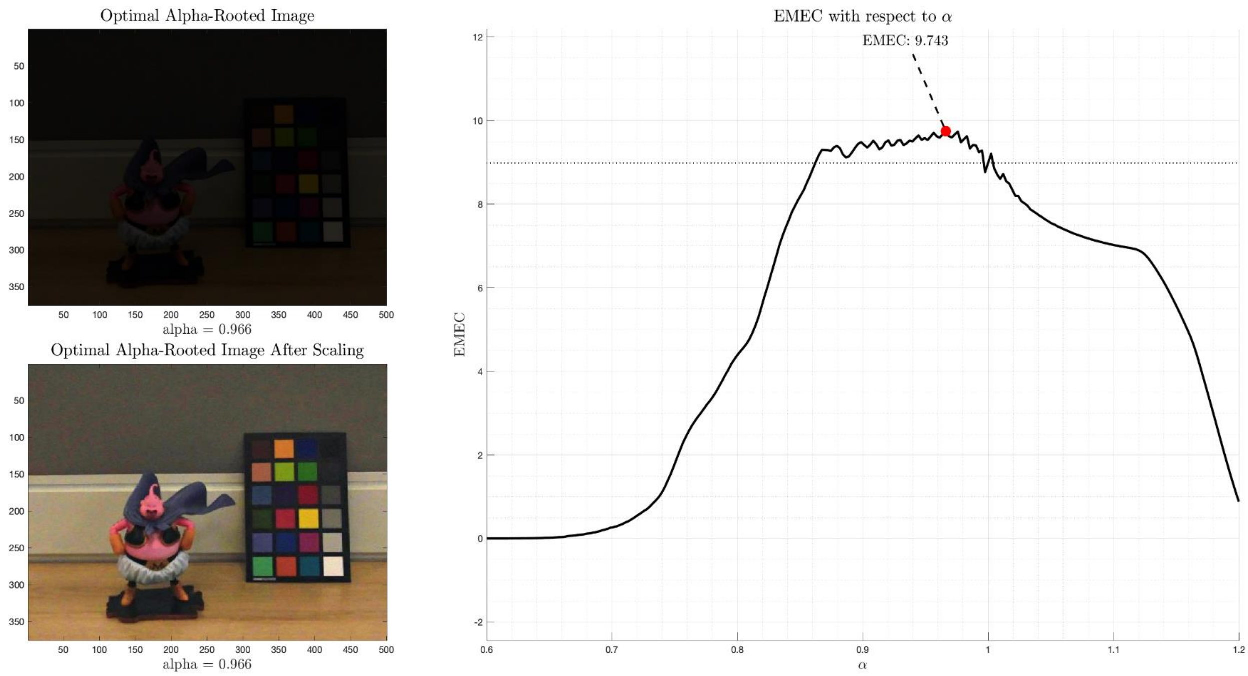


Figure 4. Alpha-rooting results in the front-facing view of the **LOM** dataset's "**buu**" scene.

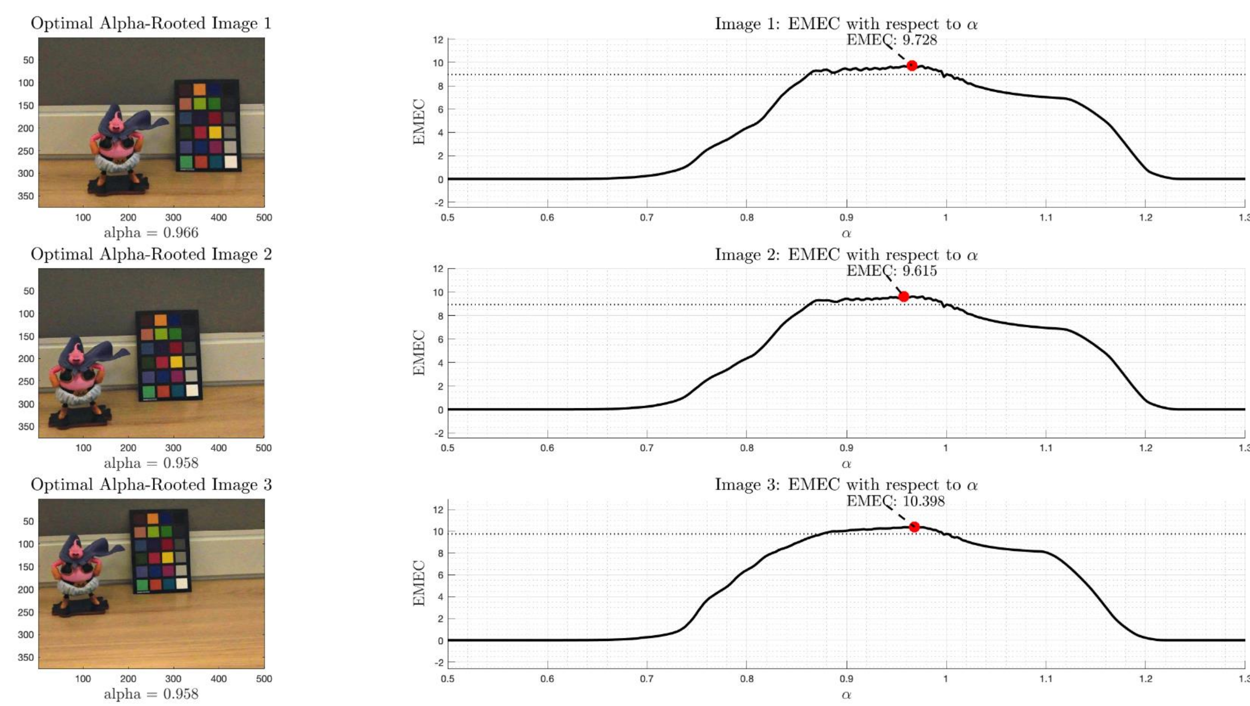


Figure 5. Multi-view 3 novel view results on **LOM** dataset's "***buu***" scene.

(a). R2L NeLF (b) RetinexNet + NeLF (c) LIME + NeLF (d) Alpha-rooting + R2L (e) Ground Truth

Figure 6. Multi-view rendering results on **LOM** dataset's "***buu***", "***sofa***", "***shrub***" and "***chair***" scenes.

Also, the further limitation of the R2L NeLF along with the deep learning-based enhancement method is that their application is scene specific based on the conditions imposed at training time. However, the most relevant discovery is that both the deep learning-based enhancements and our proposed Alpha-rooting method still struggle to maintain multi-view consistency. This has an adverse effect on the effectiveness of novel view generation by NeLF, as it leads to the easier generation of artifacts and noise. This lack of robustness by the traditional 2D enhancement methods is what the recent work by Cui et.al [7] addresses using unsupervised learning based on the effects of concealing fields.

Method	Buu		sofa		shrub		chair	
	CEME	PSNR	CEME	PSNR	CEME	PSNR	CEME	PSNR
R2L NeLF	4.23	8.91	3.12	7.44	4.74	8.11	4.33	7.77
LIME+NeLF	8.92	13.21	5.78	13.51	23.65	14.81	5.21	12.31
RetinexNet+R2L	8.51	16.16	6.77	17.65	22.41	13.76	5.55	17.81
Alpha-rooting+R2L	9.74	14.06	7.52	19.50	27.74	8.48	6.47	15.22

Table 2. CEME↑ and PSNR↑ results on the **LOM** dataset's scenes.

The Quantitative results are shown in Table 2. We set the LOM's normal lit view as the ground truth reference to compare with the baseline R2L NeLF and image enhanced R2L NeLF. The CEME↑ and PSNR↑ are reported for the selected rendered image of each scene. From the results, we see the baseline R2L NeLF performs the worst as it is not trained on Low Light Images. This results in a failure to model low-illumination-induced darkness in the wild.

Application in Mobile Pose Estimation

The results from our experiments suggest that low light image enhancement as a preprocessing step significantly improves the performance of neural light field rendering for 3D scene representation and novel view synthesis. This finding has important implications for applications such as pose estimation and biomechanical assessment, especially in low illumination conditions. By improving the quality of the input images in a video sequence, our method can help to accurately capture human motion based on the improvement of pose estimation accuracy. Other areas of study that could benefit from our method for real-time mobile applications include sports science, rehabilitation, and ergonomics, where accurate and reliable motion analysis is crucial.

Recent studies have shown the potential of neural radiance fields (NeRF) and neural light fields (NeLF) for human pose estimation and motion analysis from images and videos [15-19]. For example, Su et al. [15] proposed a NeRF-based approach relevant to 3D human pose estimation from sparse image views. Their method outperformed state-of-the-art methods on publicly available datasets. Similarly, Jiang et al. [17] developed a NeLF-based method for human motion capture from monocular video. Their method achieved comparable performance to marker-based motion capture systems, demonstrating the potential of neural rendering techniques for motion analysis. All these show Alpha-rooting can potentially help address the challenges of biomechanical assessment from low-light images.

6. CONCLUSION

In this paper, we have shown the efficiency and efficacy of the alpha-rooting by 2D-DFT for improving the quality of novel views generated from Neural Light Field rendering on Low light images. The proposed method has specifically shown promise for deployment in the wild as no training or inference is required as a preprocessing step compared to deep learning-based methods. Our preliminary experimental results show that the key to the enhancement is ensuring the optimal Alpha value is selected to modify the frequency representation of the low-light images. However, there is still much improvement to be made in applying our method to effectively handle extremely low-lit environments with non-uniform lighting conditions. This is the next challenge we aim to address and resolve.

7. ACKNOWLEDGMENT

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