Alpha-Rooting Color Image Enhancement for Neural Light Field Rendering (ARCH-NeLF)

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INTRODUCTION

The Alpha rooting color image enhancement in the frequency domain has proved to be effective for single low light image enhancement. We explore its effectiveness in improving Neural Light-Field (NeLF) Scene Representation for novel view synthesis from a single low-quality light field color image. The enhancement is achieved by processing all three-color components (R, G, B) of the image simultaneously using a Quaternion Color transformation as a hyperparameter for Neural Light Field scene representation. Thus, the proposed method is designated as **ARCH-NeLF** (ARCH; Alpha rooting correlated hyper-parametrized)

Background on 2D-DQFT for Image Enhancement

The alpha-rooting method for Color image enhancement can be described by 2-D quaternion discrete Fourier transform (2-D DQFT) followed by spatial transformation. Then, EME and CEME are used as Measure estimates to verify the level of image enhancement

Fig. 1 Original Image

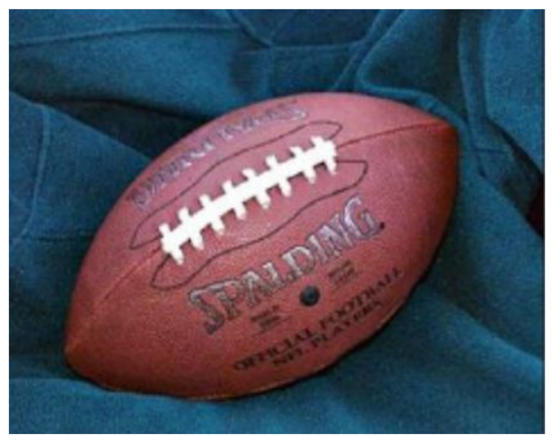

Fig. 2 Enhanced image using Alpha-rooting by 2-D DQFT

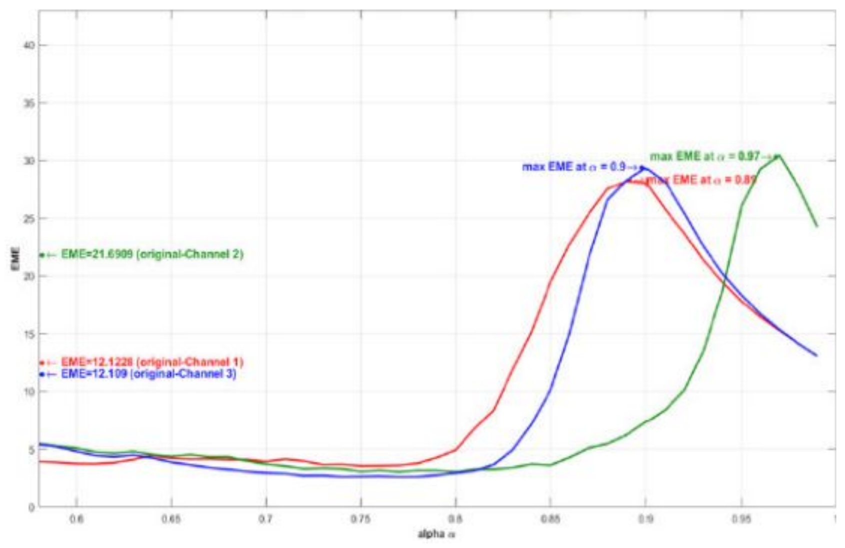

Fig. 3 Plot of EME vs alpha for alpha-rooting by 2-D DQFT for each channel (R,G,B)

"football.jpg"	Alpha	EME	CEME
Original Image	-	R: 12.1228	25.7068
		G: 21.6919	
		B: 12.1091	
2-D DQFT Alpha-Rooting	0.95	-	40.20035
2-D DQFT Alpha-Rooting With Spatial Transformation	0.95	-	45.1754
2-D DFT Alpha-Rooting	R: 0.87	25.1773	37.2225
	G: 0.97	22.3891	
	B:0.91	19.5084	
2-D DFT Alpha-Rooting with Spatial Transformation	R: 0.87	-	40.9294
	G:0.97	-	
	B:0.91	-	

From the EME plot vs alpha and table for the image "football.jpg" in Fig. 3, we see that the best value of alpha for channels red, green and blue are 0.87, 0.97, and 0.91 respectively to get 0.95 for the 2D-DQFT

METHODS

Color Image Enhancement Method Using the 2-D DQFT based on Quaternion Algebra

Quaternion numbers are four-dimensional hyper-complex numbers that are represented in Cartesian form as:

q = ai + jb + kc

The color image can be represented in the quaternion space by three or four channels. In the case of three channel color models like the RGB, or XYZ, the color images can be represented as pure quaternions.

$$f(n, m) = R(n, m)i + G(n, m)j + B(n, m)k.$$

Then, the 2D-DQFT of the color image $f_{n,m}$ is considered of the size N × M × 3. represented by the equation below

$$F_{p,s} = \sum_{n=0}^{N-1}\sum_{m=0}^{M-1} W_j^{np} f_{n,m} W_k^{ms} = \sum_{n=0}^{N-1} W_j^{np}\left(\sum_{m=0}^{M-1} f_{n,m} W_k^{ms}\right), \quad p=0:(N-1),\ s=0:(M-1).$$

Light Field Rendering Method Using the 5-D LF based on the Plenoptic Function of the Radiance Field

Neural Light Field (NeLF) **presents a more structured representation over NeRF in novel view synthesis as the rendering of a pixel amounts to one single forward pass without ray-marching. By operating on a four-dimensional representation of the light field, the model learns to represent view-dependent effects accurately. More so, By enforcing geometric constraints during training and inference, the scene geometry is implicitly learned from a sparse set of views. we use a two-stage transformer-based model that first aggregates features along epipolar lines, then aggregates features along reference views to produce the color of a target ray.**

$$\beta^j = \frac{\exp\left(W_2\left[\hat{r} \parallel \tilde{z}^j\right]\right)}{\sum_k \exp\left(W_2\left[\hat{r} \parallel \tilde{z}^k\right]\right)}, \qquad c_{\text{aux}} = \sum_j \beta^j \left(\sum_i \alpha_i^j c_i^j\right)$$

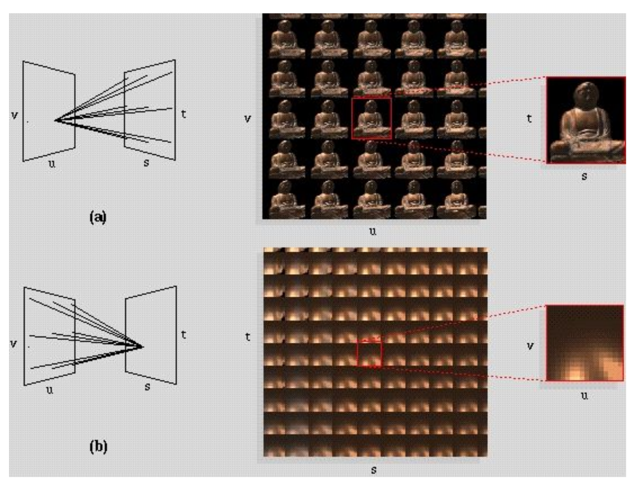

Fig. 4 Storing 4D light field data as flat 2D array

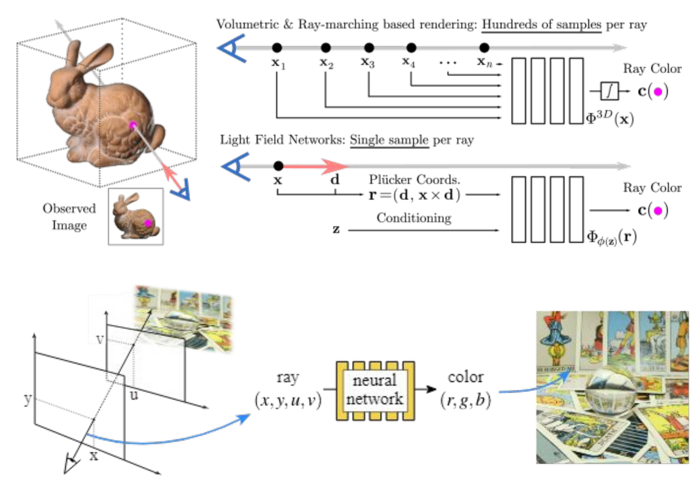

Fig.5 3D-structured Light Field Neural Scene Representations

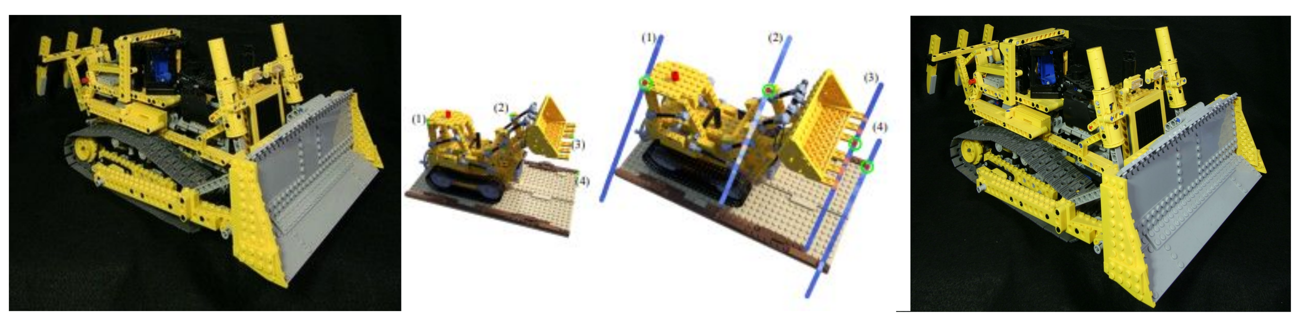

Fig. 6 Correspondence Distribution of The per-point attention weights learned by the model to the target ray for rendering

RESULTS

The Alpha rooting correlation by 2D-DQFT achieves state of the art results in 3D Novel view synthesis from light field Images of low light condition as compared to their High Resolution ground truth versions. Extensive experiments on both synthetic and real-world scenes show the merits of our ARCH-NELF method over other radiance algorithms.

Qualitative Results of the ARCH-NeLF (Refined)

Fig. 9 Original low light Flower image

Fig. 10 ARCH Flower Image Enhancement

Fig. 11 ARCH-NeLF Novel view rendering

Quantitative Results of the ARCH-NeLF (Referenced)

Model	PSNR [DB] ↑	SSIM ↑	LPIPS ↑	Avg. ↓
LLFF	24.41	0.863	0.211	0.0656
NeRF	26.76	0.883	0.246	0.0562
IBRNet	26.73	0.851	0.175	0.0523
NeX	27.26	0.904	0.178	0.0473
LF-Nelf	28.26	0.920	0.062	0.0297
ARCH	28.26	0.921	0.059	0.0293

Fig. 7 Results for the real forward -facing (RFF) dataset from the source paper on LF-NeLF

Model	PSNR [DB] ↑	SSIM ↑	LPIPS ↑	Avg. ↓
Vanilla-NLF	17.39	0.614	0.516	0.1802
1-MLP	21.33	0.774	0.208	0.0900
2-MLP	26.16	0.896	0.076	0.0390
No CNN (v^j_i)	27.43	0.910	0.057	0.0314
No 3D Coordinates	28.17	0.920	0.047	0.0273
No LCE (k_j)	28.23	0.926	0.045	0.0264
Mean Pooling	28.39	0.929	0043	0.0255
No Auxiliary Loss	28.43	0.931	0.043	0.0253
LF-NeLF	28.78	0.934	0.034	0.0235
ARCH	28.74	0.932	0.035	0.0233

Fig. 8 Ablation study on the LF dataset, with 25 % the original resolution (504 × 378) after ARCH.

CONCLUSIONS

1. **ARCH is proven efficient for the low light Image enhancements.**
2. **ARCH achieves similar Results to the LF-NeLF Ground Truth.**
3. **ARCH achieved better NeLF by RGB Hyper-Parametrization.**
4. **ARCH can be used for the enhancement of Medical Images.**

For the first time, we show Alpha Rooting Color Image enhancement by the 2D-DQFT followed by spatial transformations is effective for enhancing NeLF rendering from low light Images, as the quaternion approach gives a color to the low light image that is closer to the original image. Thus, improving the Light field rendering fidelity

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