#### $K\Lambda IS1$ Refined Tensorial Radiance Field: Harnessing Coordinate-Based Networks for Novel View Synthesis from Sparse Inputs

Optimization and Statistical Inference LAB

## Introduction

The multi-plane encoding approach allows NeRFs to learn fine-grained details rapidly and achieves outstanding performance, however, it has limitations in representing the global context of the scene such as object shapes and dynamic motion over times when available training data is sparse.

In this work, we propose refined tensorial radiance fields that harness coordinate-based networks capturing low-frequency signals, while multi-plane network focuses on fine-grained details simultaneously. Empirically, the proposed outperform all baselines for the task with static and dynamic scenes under sparse inputs.

### Motivation

The multi-plane encoding with TV loss still struggles to represent global context in the sparse-inputs (HexPlane, CVPR2023).



T=0.0







T=0.7T=0.5HexPlane (CVPR2023)



T=0.0



T=0.2



T=0.7



#### Mingyu Kim<sup>1</sup>, Jun-Seong Kim<sup>2</sup>, Se-Young Yun<sup>1</sup> and Jin-Hwa Kim<sup>3</sup>

KAIST AI<sup>1)</sup>, POSTECH EE<sup>2)</sup>, NAVER AI Lab. & SNU AIIS<sup>3)</sup> {callingu, yunseyoung}@kaist.ac.kr, gucka28@postech.ac.kr, j1nhwa.kim@navercorp.com

Method





# with multi-plane grid features.





## **Quantitative Results**

#### Evaluation on Static NeRF dataset (8 views)

| Models          | PSNR ↑       |              |       |              |              |              |              |              | Avg.         |
|-----------------|--------------|--------------|-------|--------------|--------------|--------------|--------------|--------------|--------------|
|                 | chair        | drums        | ficus | hotdog       | lego         | materials    | mic          | ship         | PSNR '       |
| Simplified_NeRF | 20.35        | 14.19        | 21.63 | 22.57        | 12.45        | 18.98        | 24.95        | 18.65        | 19.22        |
| DietNeRF        | 21.32        | 14.16        | 13.08 | 11.64        | 16.12        | 12.20        | 24.70        | 19.34        | 16.57        |
| HALO            | 24.77        | 18.67        | 21.42 | 10.22        | 22.41        | 21.00        | 24.94        | 21.67        | 20.64        |
| FreeNeRF        | 26.08        | <u>19.99</u> | 18.43 | <u>28.91</u> | 24.12        | <u>21.74</u> | 24.89        | <u>23.01</u> | 23.40        |
| DVGO            | 22.35        | 16.54        | 19.03 | 24.73        | 20.85        | 18.50        | 24.37        | 18.17        | 20.57        |
| VGOS            | 22.10        | 18.57        | 19.08 | 24.74        | 20.90        | 18.42        | 24.18        | 18.16        | 20.77        |
| iNGP            | 24.76        | 14.56        | 20.68 | 24.11        | 22.22        | 15.16        | 26.19        | 17.29        | 20.62        |
| TensoRF         | 26.23        | 15.94        | 21.37 | 28.47        | 26.28        | 20.22        | 26.39        | 20.29        | 23.15        |
| K-Planes        | <u>27.30</u> | 20.43        | 23.82 | 27.58        | <u>26.52</u> | 19.66        | 27.30        | 21.34        | <u>24.24</u> |
| Ours            | 28.02        | 19.55        | 20.30 | 29.25        | 26.73        | 21.93        | <u>26.42</u> | 24.27        | 24.56        |

Qualitatively, the proposed method enables to represent both lowfrequency and high-frequency details simultaneously, whereas baselines inevitably suffer from performance issues due to artifacts **K-Planes** 







We developed a new method where the coordinate network captures global context, like object shapes and dynamic motions, and it also incorporates multi-plane encoding to precisely describe the finest details.





## **Qualitative Results**



While baselines struggle to learn consistently with varying TV regularization. the proposed method effectively handles novel-view synthesis, leading to reliable performance regardless of the regularization.

### Conclusion