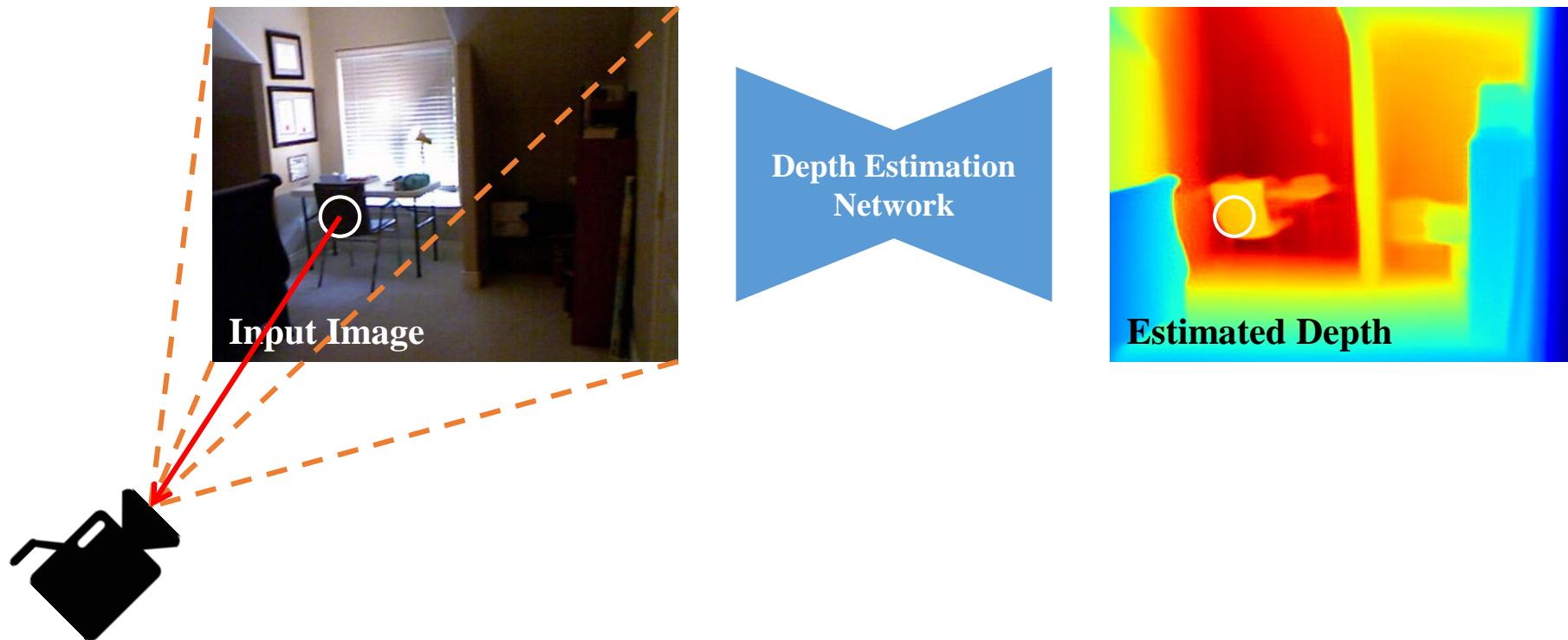




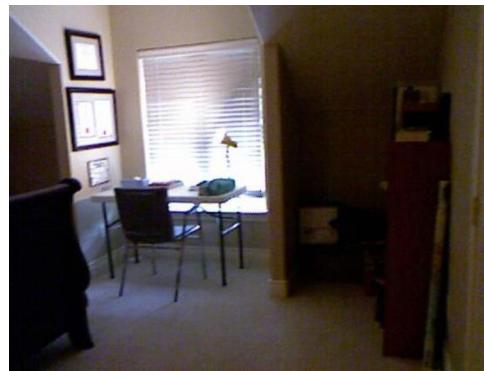
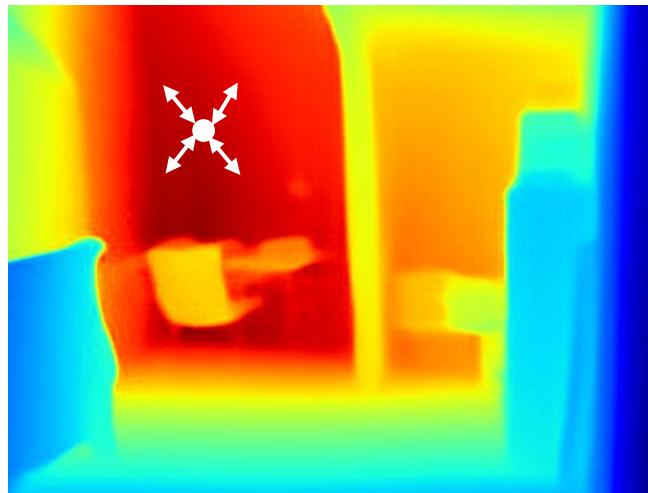
DCDepth: Progressive Monocular Depth Estimation in Discrete Cosine Domain

Kun Wang, Zhiqiang Yan, Junkai Fan, Wanlu Zhu, Xiang Li, Jun Li and Jian Yang

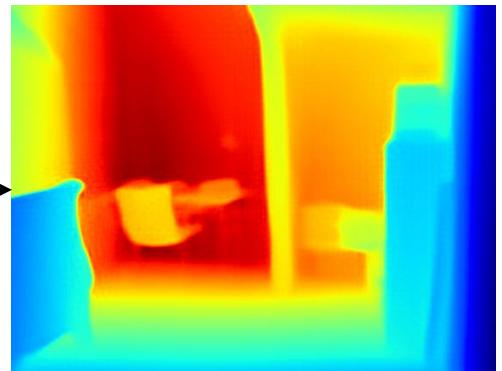
Monocular Depth Estimation



Limitations of Existing Works



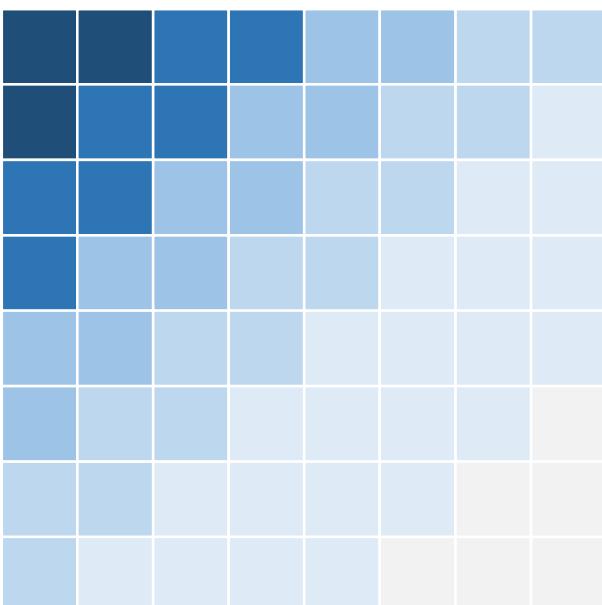
Single
feed forward



- Unable to model the local correlations.
- Hard to manage complex scenes.

Introduction to 2D Discrete Cosine Transform (DCT)

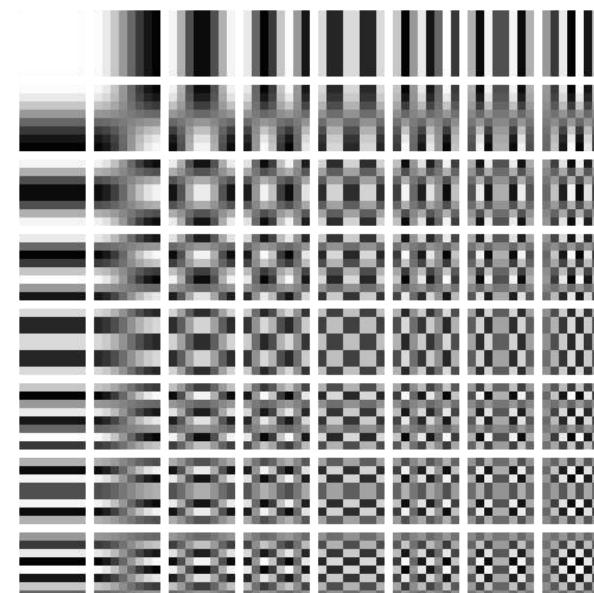
Higher Frequency



Frequency Spectrum
($S \times S$)



Multiply
&
Sum



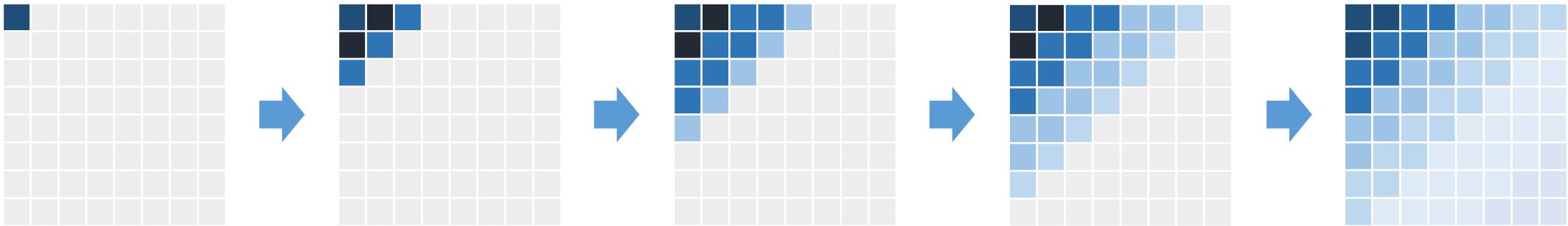
Basis Functions
($S \times S$)



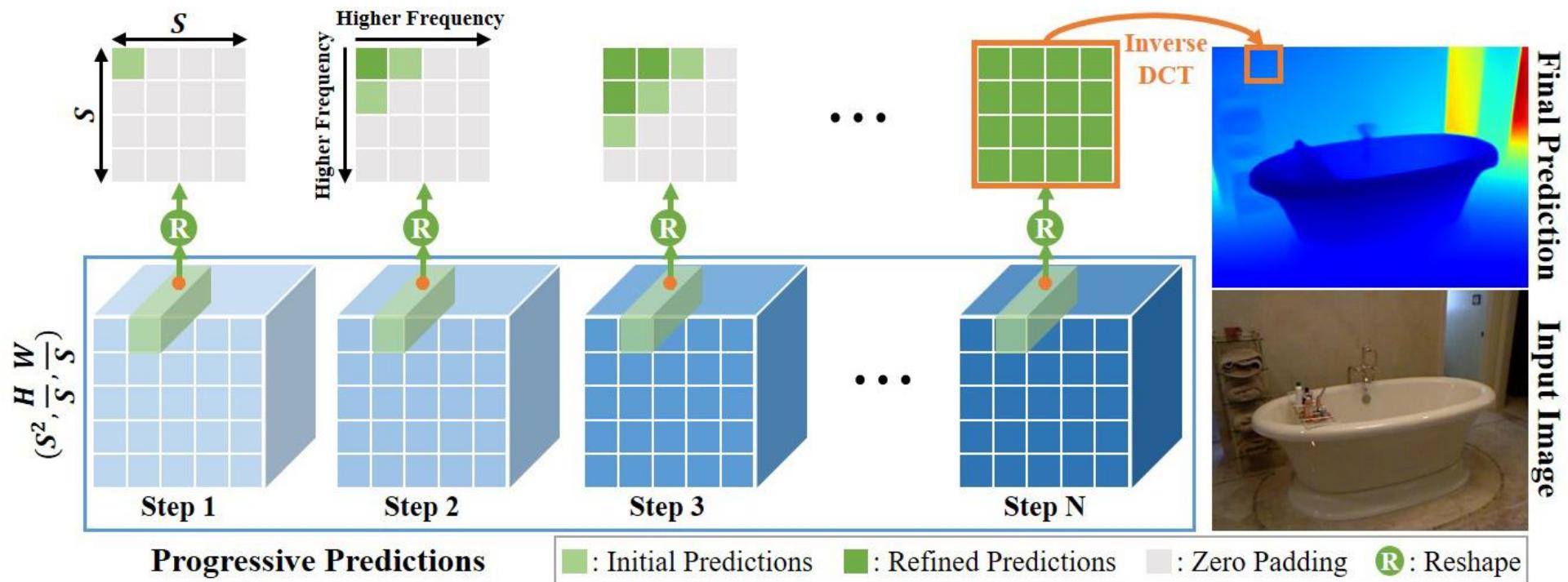
Image
($S \times S$)

Introduction to 2D Discrete Cosine Transform (DCT)

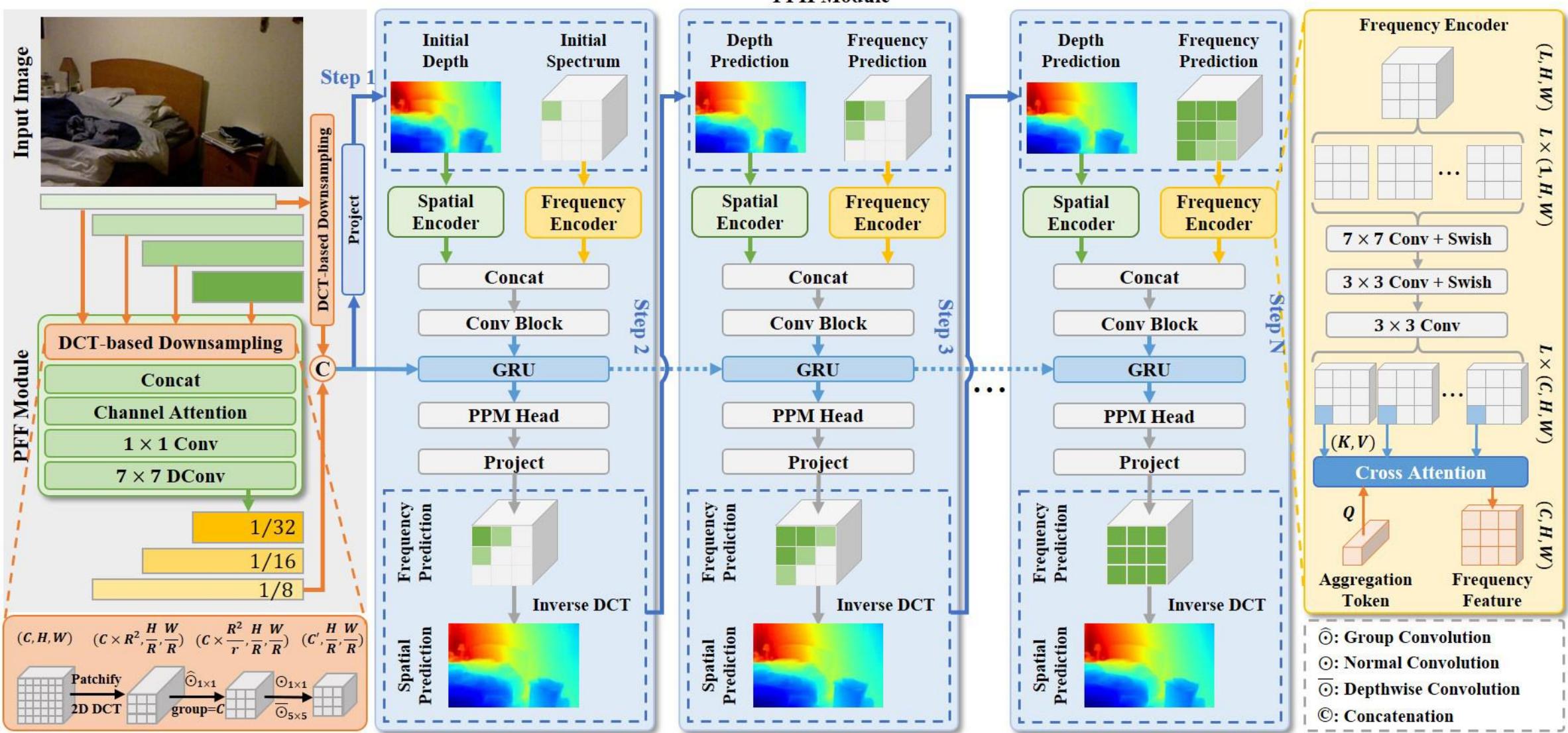
: Zero Padding



Progressive Estimation Scheme



Network Architecture



Training Loss

- **Scale-Invariant Log Loss**

$$L_d = \alpha \cdot \sum_{i=1}^N \beta^{N-i} \sqrt{\frac{1}{M} \sum d_i^2 - \frac{\lambda}{M^2} (\sum d_i)^2},$$

- **Frequency Regularization Term**

$$L_f = \sum (\epsilon^{u+v} - 1) \cdot |f_{u,v}|,$$

- **Smoothness Regularization Term**

$$L_s = |\partial_x \hat{\mathcal{D}}| \cdot e^{-|\partial_x I_t|} + |\partial_y \hat{\mathcal{D}}| \cdot e^{-|\partial_y I_t|},$$



Quantitative Result

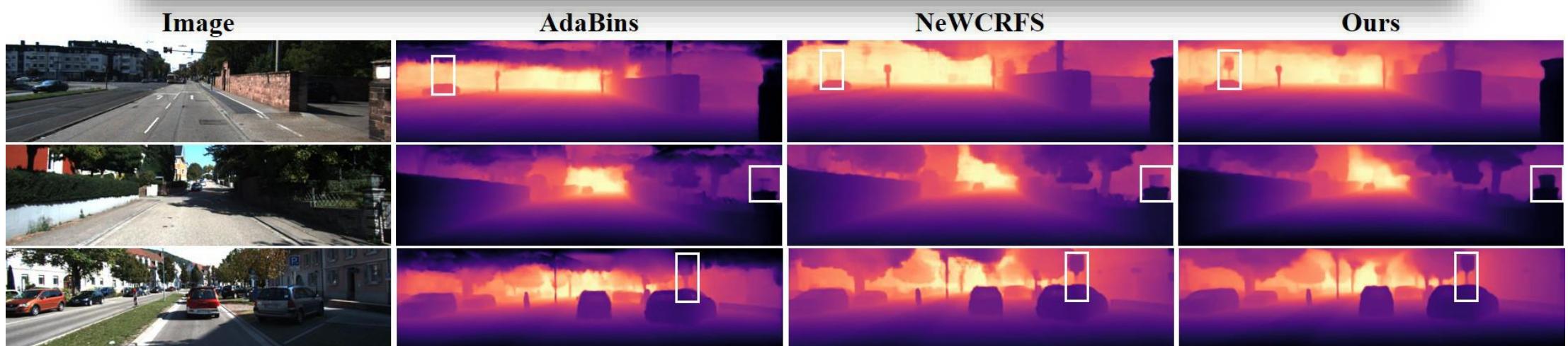
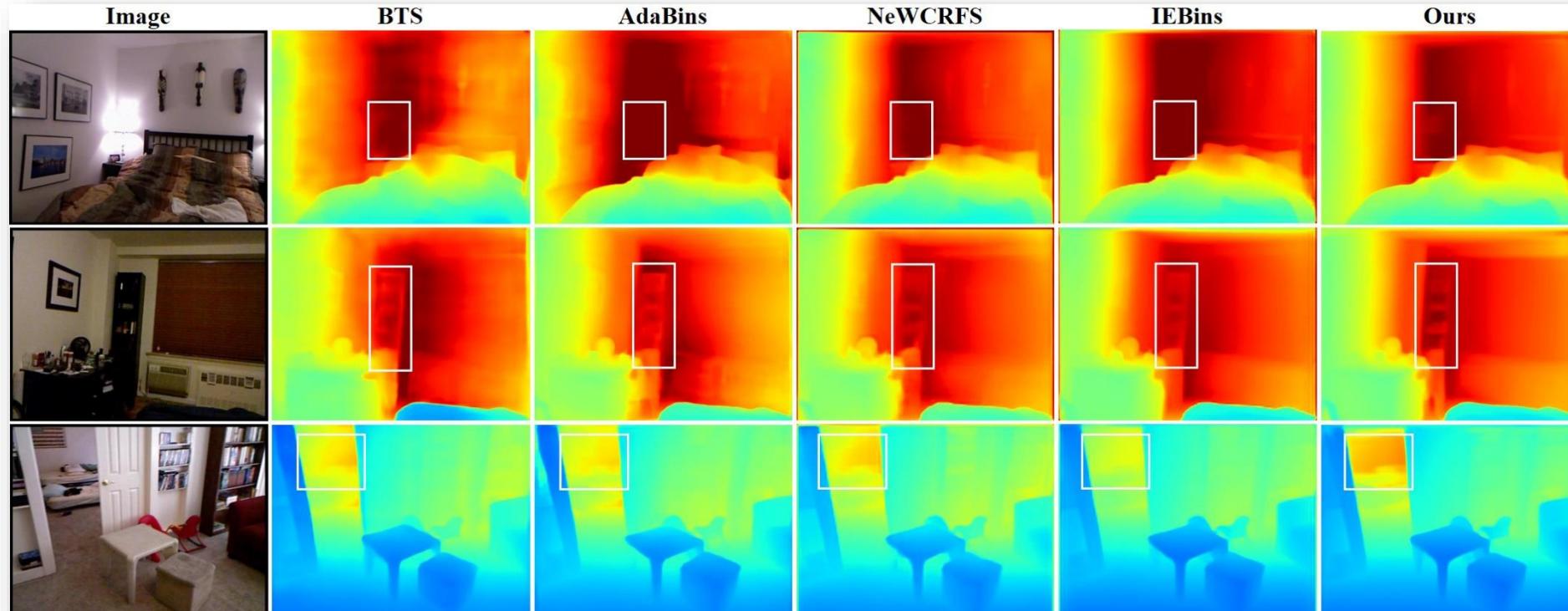
NYU-Depth-V2

Method	Backbone	Abs Rel ↓	Sq Rel ↓	RMSE ↓	$\log_{10} \downarrow$	$\delta < 1.25 \uparrow$	$\delta < 1.25^2 \uparrow$	$\delta < 1.25^3 \uparrow$
DORN [12]	ResNet-101	0.115	–	0.509	0.051	0.828	0.965	0.992
VNL [55]	ResNet-101	0.108	–	0.416	0.048	0.875	0.976	0.994
BTS [17]	DenseNet-161	0.110	0.066	0.392	0.047	0.885	0.978	0.994
ASNDepth [24]	HRNet-48	0.101	–	0.377	0.044	0.890	0.982	0.996
TransDepth [54]	R-50+ViT-B/16	0.106	–	0.365	0.045	0.900	0.983	0.996
AdaBins [3]	E-B5+mini-ViT	0.103	–	0.364	0.044	0.903	0.984	<u>0.997</u>
LocalBins [4]	E-B5	0.099	–	0.357	0.042	0.907	0.987	0.998
NeWCRFS [58]	Swin-Large	0.095	0.045	0.334	0.041	0.922	0.992	0.998
BinsFormer [20]	Swin-Large	0.094	–	0.330	0.040	0.925	0.989	<u>0.997</u>
PixelFormer [11]	Swin-Large	0.090	–	0.322	0.039	0.929	<u>0.991</u>	0.998
IEBIns [34]	Swin-Large	0.087	<u>0.040</u>	0.314	<u>0.038</u>	0.936	0.992	0.998
MG-Depth [21]	Swin-Large	0.087	–	<u>0.311</u>	–	0.933	–	–
NDDepth [33]	Swin-Large	0.087	0.041	<u>0.311</u>	<u>0.038</u>	0.936	<u>0.991</u>	0.998
VA-DepthNet [22]	Swin-Large	<u>0.086</u>	0.039	0.304	0.037	<u>0.937</u>	0.992	0.998
Ours	Swin-Large	0.085	0.039	0.304	0.037	0.940	0.992	0.998

KITTI-Eigen

Method	Backbone	Abs Rel ↓	Sq Rel ↓	RMSE ↓	RMSE log ↓	$\delta < 1.25 \uparrow$	$\delta < 1.25^2 \uparrow$	$\delta < 1.25^3 \uparrow$
DORN [12]	ResNet-101	0.072	0.307	2.727	0.120	0.932	0.984	0.994
VNL [55]	ResNet-101	0.072	–	3.258	0.117	0.938	0.990	<u>0.998</u>
BTS [17]	DenseNet-161	0.060	0.249	2.798	0.096	0.955	0.993	<u>0.998</u>
TransDepth [54]	R-50+ViT-B/16	0.064	0.252	2.755	0.098	0.956	0.994	0.999
AdaBins [3]	E-B5+mini-ViT	0.058	0.190	2.360	0.088	0.964	<u>0.995</u>	0.999
P3Depth [26]	ResNet-101	0.071	0.270	2.842	0.103	0.953	0.993	<u>0.998</u>
NeWCRFS [58]	Swin-Large	0.052	0.155	2.129	0.079	0.974	0.997	0.999
BinsFormer [20]	Swin-Large	0.052	0.151	2.096	0.079	0.974	0.997	0.999
PixelFormer [11]	Swin-Large	<u>0.051</u>	0.149	2.081	<u>0.077</u>	<u>0.976</u>	0.997	0.999
VA-DepthNet [22]	Swin-Large	0.050	<u>0.148</u>	2.093	0.076	0.977	0.997	0.999
iDisc [27]	Swin-Large	0.050	0.145	<u>2.067</u>	<u>0.077</u>	0.977	0.997	0.999
Ours	Swin-Large	<u>0.051</u>	0.145	2.044	0.076	0.977	0.997	0.999

Qualitative Result





Thank You!
感谢您！

