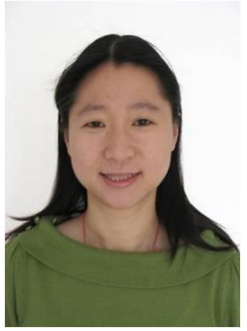
25th INTERNATIONAL CONFERENCE ON PATTERN RECOGNITION
Milan, Italy 10 | 15 January 2021

Multi-scale Residual Pyramid Attention Network for Monocular Depth Estimation



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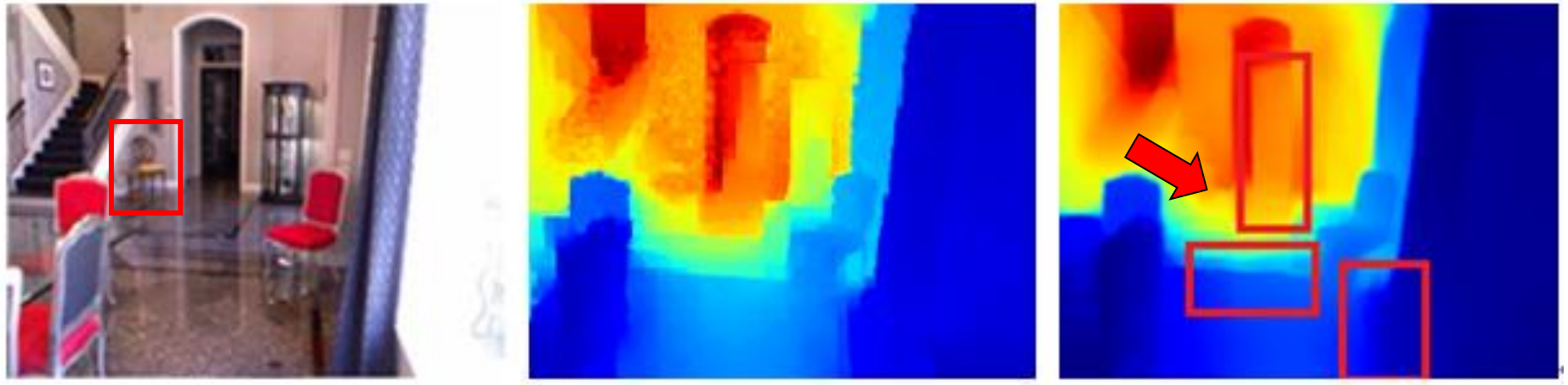
Contents

Introduction

- Existing methods fail to consider complex textures and geometries in scenes.



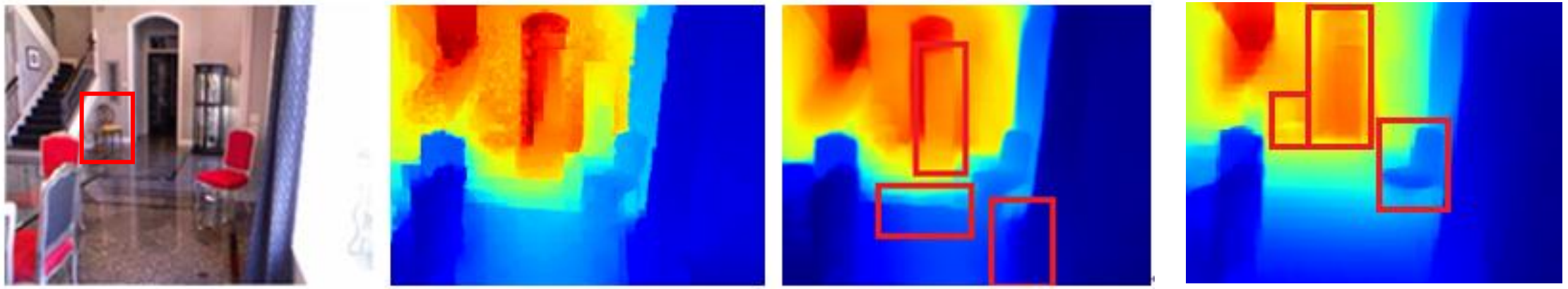
RGB GT Hu et al.[9]

Problems:

loss of local details, distorted object boundaries, and blurry reconstruction.

Introduction

- In this work, we proposed an end-to-end multi-scale residual pyramid attention network.

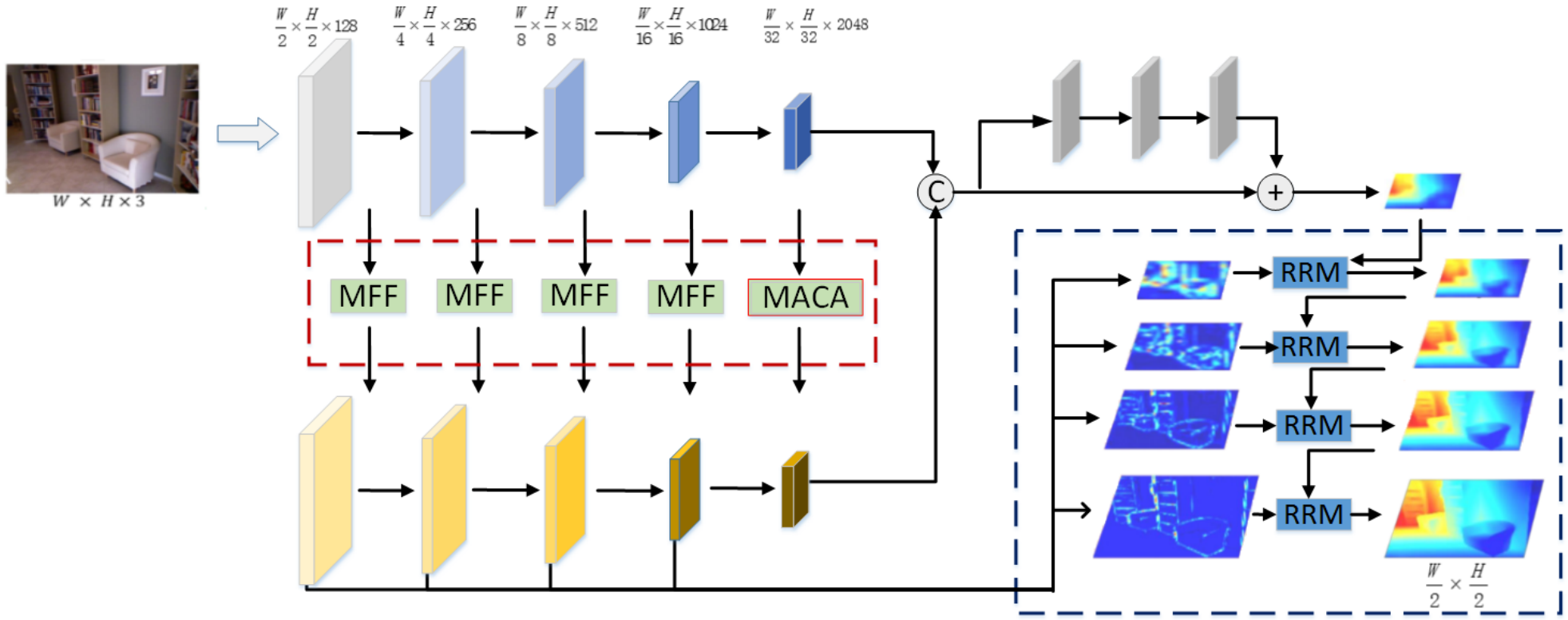


RGB GT Hu et al.[9] Ours

Our method achieved competitive performance in object boundaries and local details.

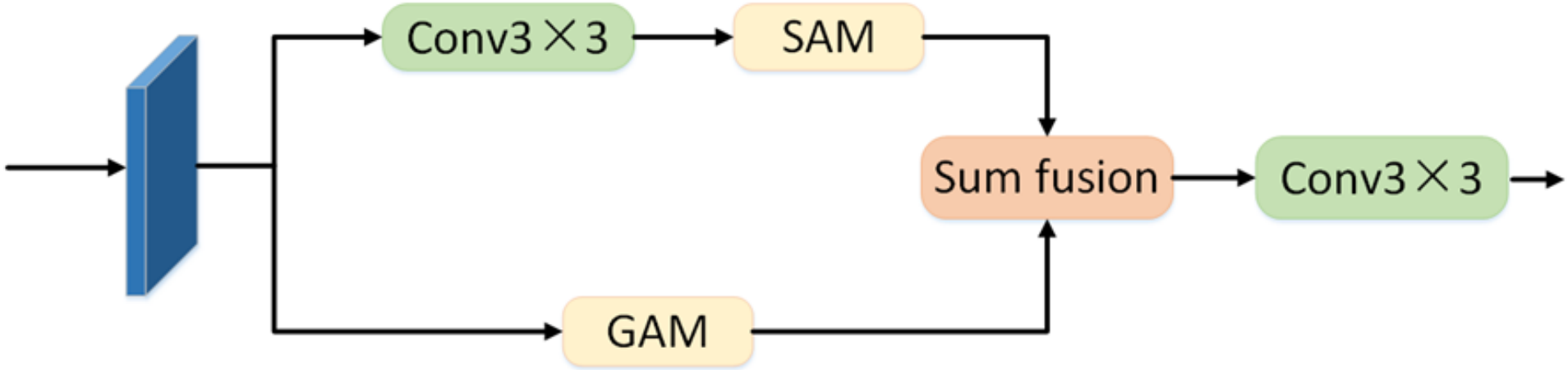
Method

- The proposed network architecture:



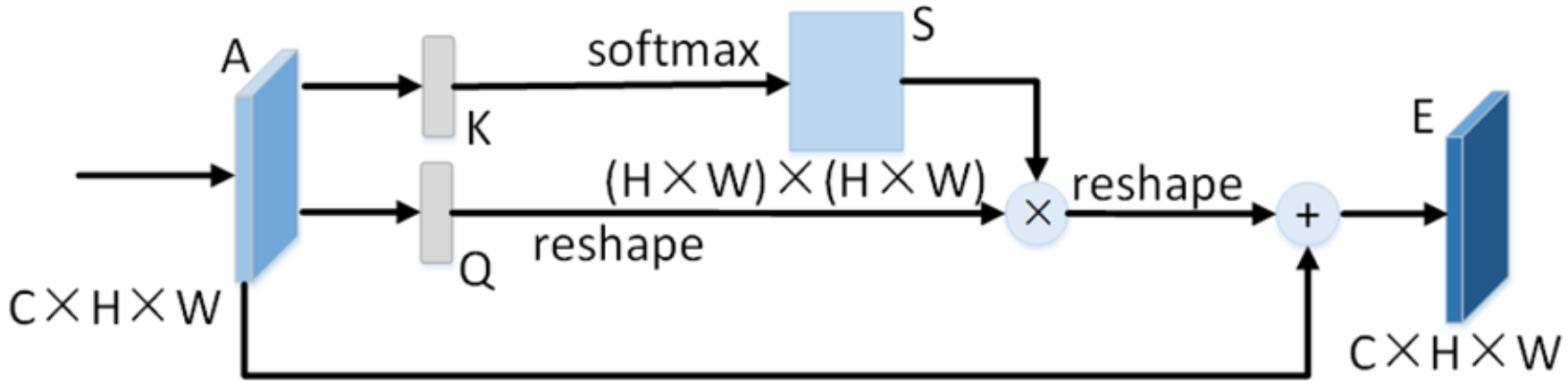
Method

- Multi-scale attention context aggregation (MACA)
  - We proposed MACA, the module consists of SAM and GAM, which adaptively learns the similarities between pixels to aggregation the spatial and scale context information.



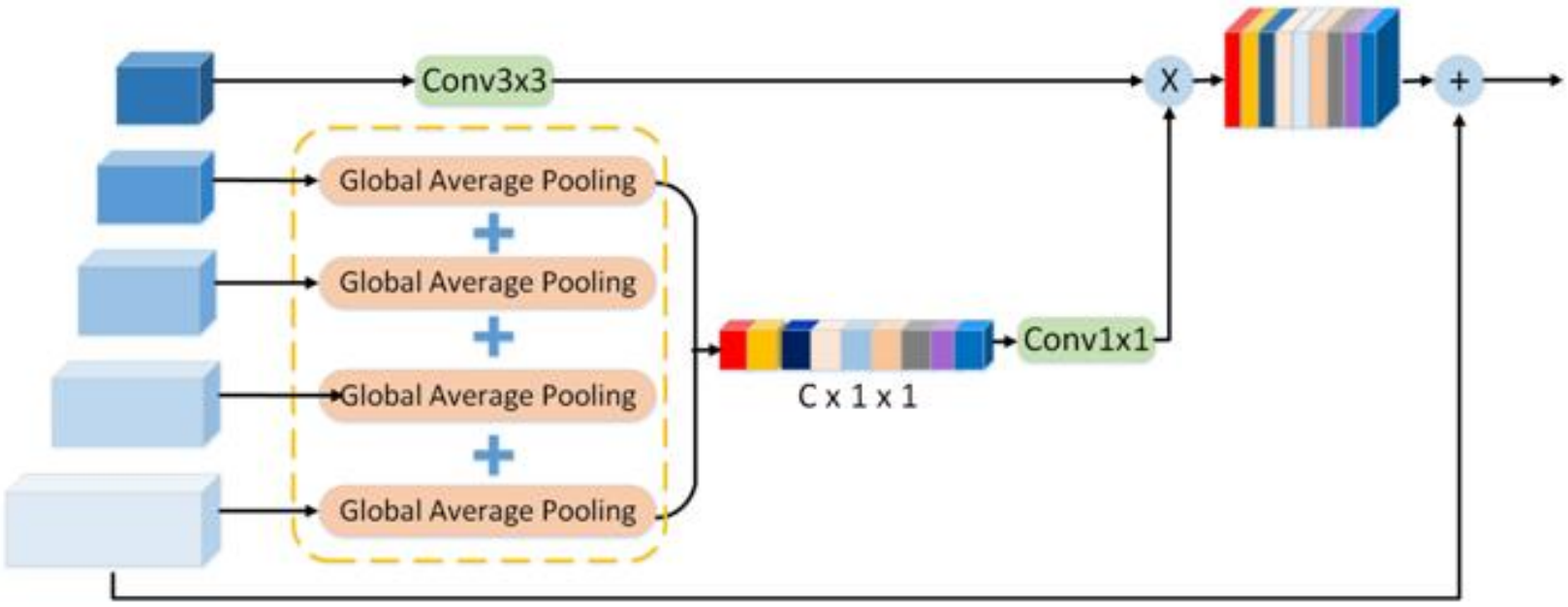
Method

- Spatial attention module (SAM)



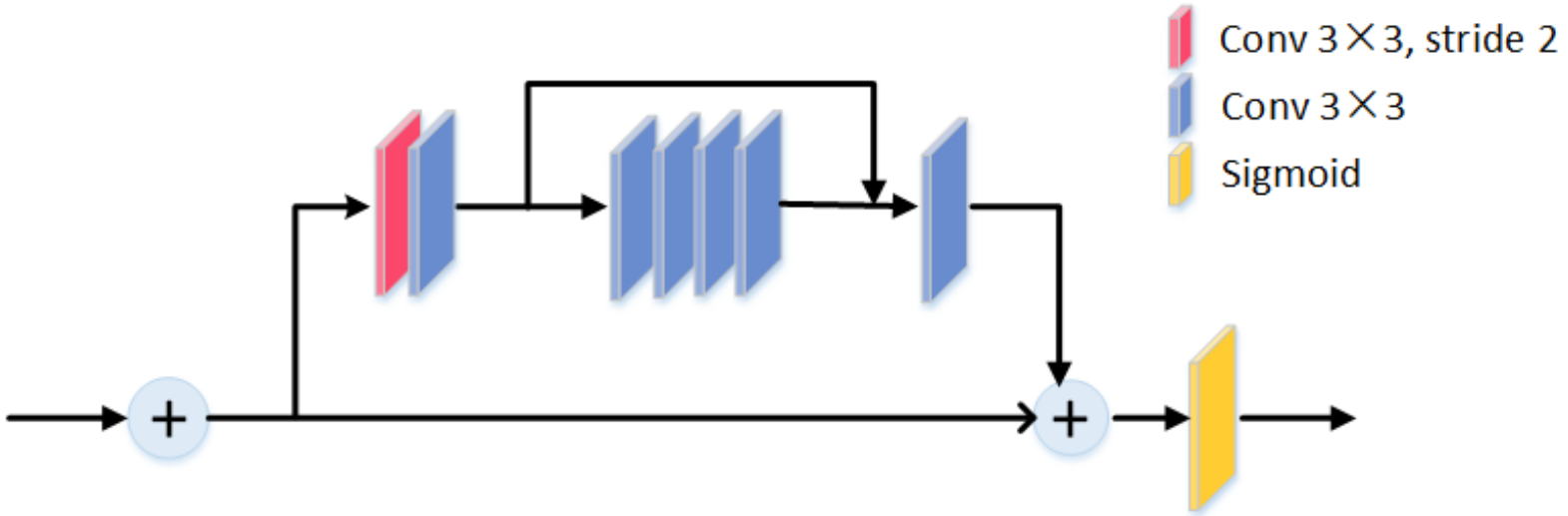
Method

- Global attention module (GAM)



Method

- Residual refinement module (RRM)
  - Improved RRM, the module can capture more details information to further refine the scene structure.



Method

- Computed the difference between the predicted depth map D^i and the ground-truth G^i at each scale. Combing all the L scales, our loss function for the entire network is:

$$Loss = \sum_{i=1}^{L} (l_{depth}^{i} + l_{grad}^{i} + l_{normal}^{i})$$

For each scale, It consists of three terms:

l_{depth} considering the pixel-wise difference between D^i and the ground truth G^i.

l_{grad} penalizing errors around edges.

l_{normal} further improving fine details.

Experiment Results

- Implementation Details

  - Initialize the encoder module by pre-trained model on ImageNet, use SENet as the backbone.
  - Adam optimizer with initial learning rate 10^{-4}, reduce 10% every 5 epoch. $\beta 1 = 0.9$, $\beta 2 = 0.999$ and weight decay as 10^{-4}.
  - Network was trained for 20 epochs with a batch size of 4.

Experiment Results

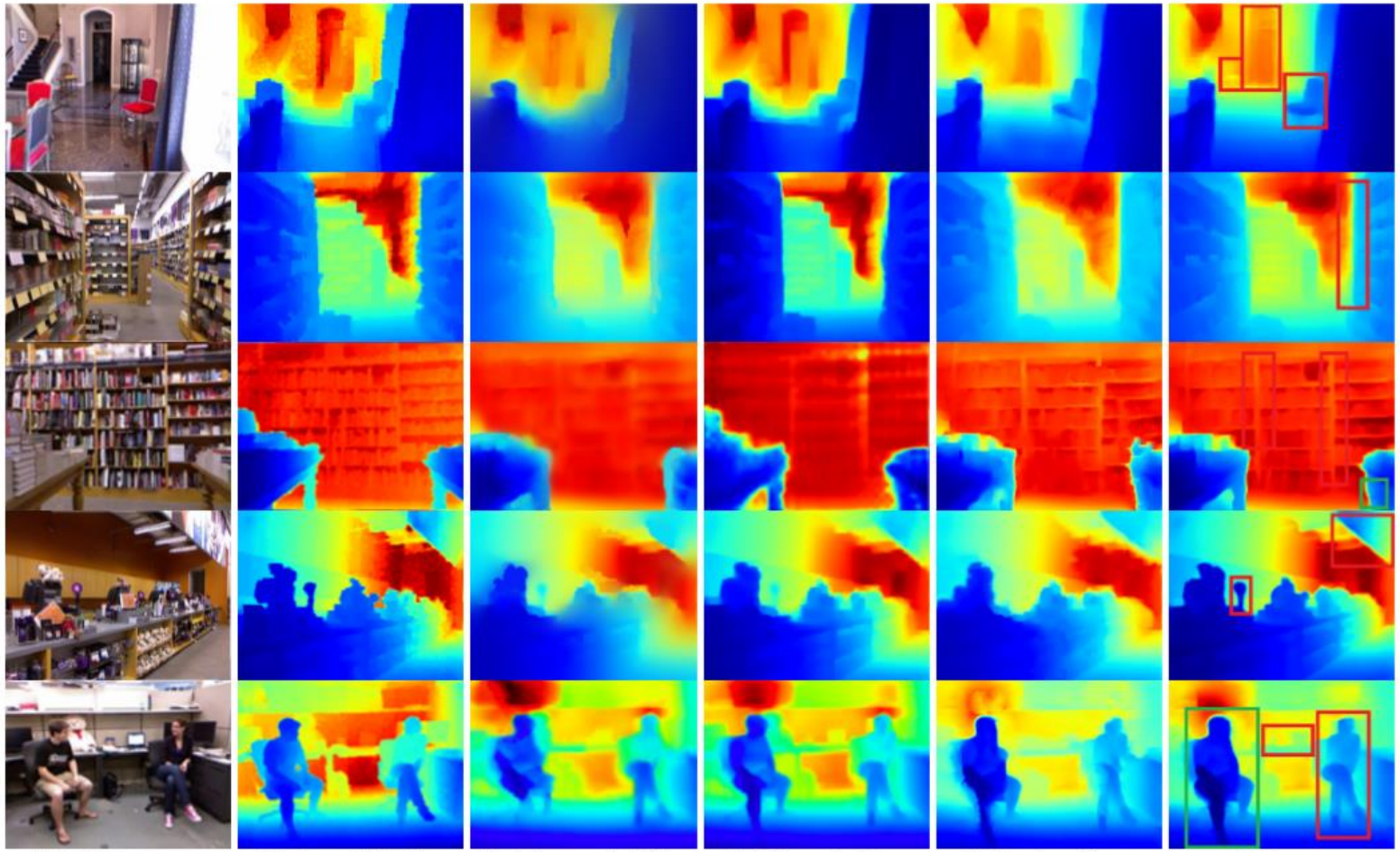
- Quantitative Evaluation(NYU Depth V2)

TABLE I
COMPARISONS WITH STATE-OF-THE-ART DEPTH ESTIMATION APPROACHES ON NYU DEPTH V2 DATASET.

Method	lower is better			higher is better		
	Abs Rel	RMS	Log10	$\sigma < 1.25$	$\sigma < 1.25^2$	$\sigma < 1.25^3$
Eigen et al. [12]	0.215	0.907	–	0.611	0.887	0.971
Laina et al. [14]	0.127	0.573	0.055	0.811	0.953	0.988
Xu et al. [26]	0.125	0.593	0.057	0.806	0.952	0.986
Chen et al. [20]	0.138	0.496	–	0.826	0.964	0.990
Fu et al. [16]	0.115	0.509	0.051	0.828	0.965	0.992
Jiao et al. [17]	**0.098**	**0.329**	**0.040**	**0.917**	**0.983**	**0.996**
Hu et al. [9]	0.115	0.530	0.050	0.866	0.975	0.993
Ding et al. [19]	0.101	0.519	0.044	0.847	0.967	0.992
Our Baseline	0.123	0.596	0.056	0.838	0.968	0.992
Our Baseline + MACA	0.121	0.537	0.051	0.854	0.973	0.993
Ours: Baseline + MACA + RRM	0.113	0.525	0.049	0.872	0.974	0.993

Experiment Results

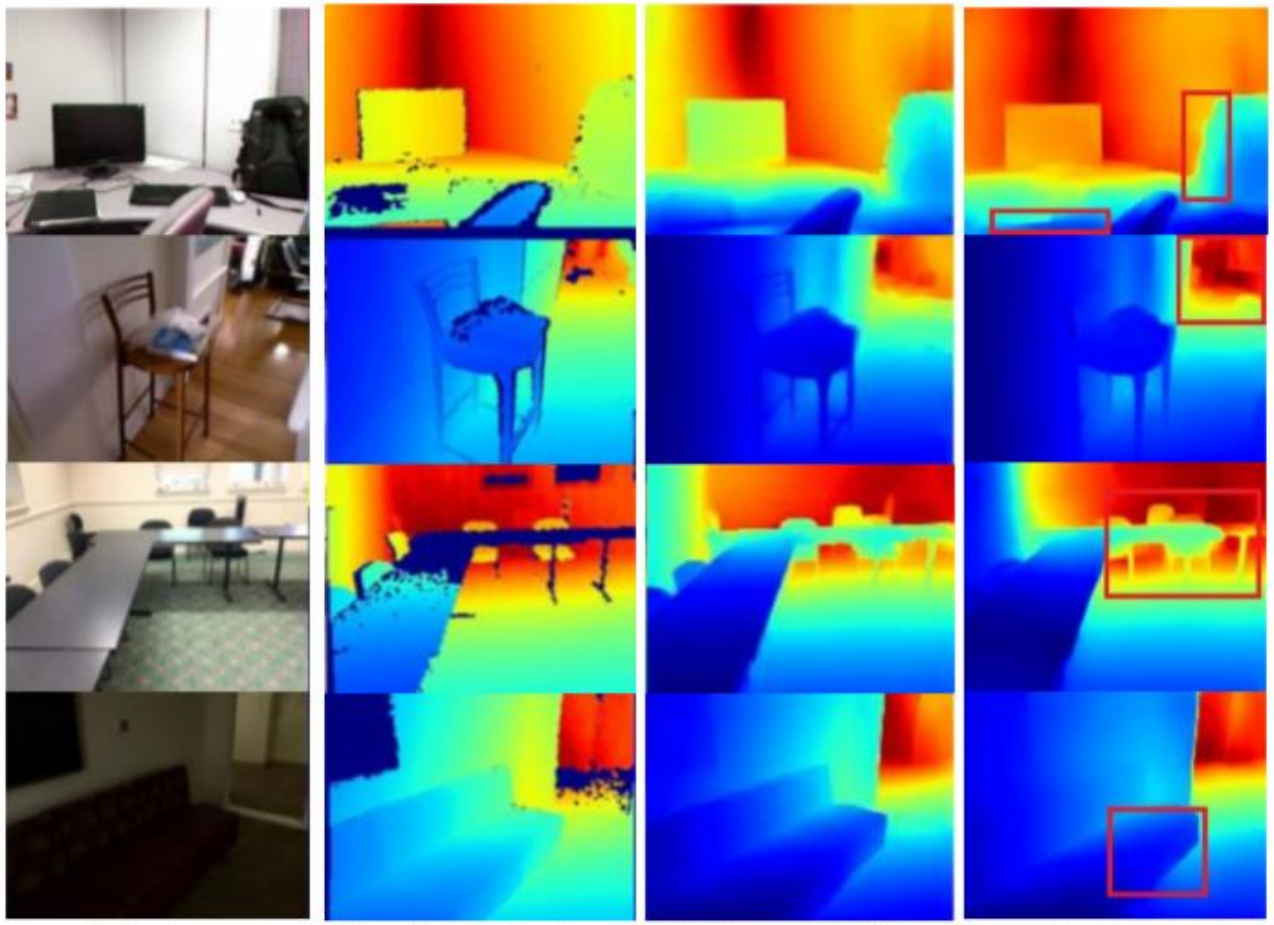
- Qualitative Evaluation(NYU Depth V2)



(a) RGB Image (b) Ground Truth (c) Laina et al. [14] (d) Hu et al. [9] (e) Our baseline (f) Ours

Experiment Results

- Qualitative Evaluation(SUN-RGBD)



(a) RGB Image (b) Ground Truth (c) Chen et al. [21] (d) Ours

Conclusion

- We proposed an MRPAN for monocular depth estimation.
- Achieves competitive performance in comparsion with the state-of-the-art methods, especially the boundaries and local details of image in complex scenes.

Thanks !
Q&A