Extending Single Beam Lidar To Full Resolution By Fusing with Single Image Depth Estimation

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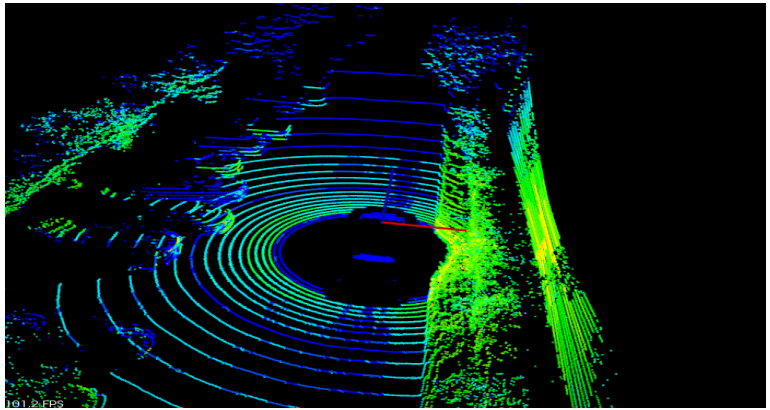
Outline

1. Limitations
2. Contribution
3. Methodology
4. Experimental Results
5. Conclusion

Limitations

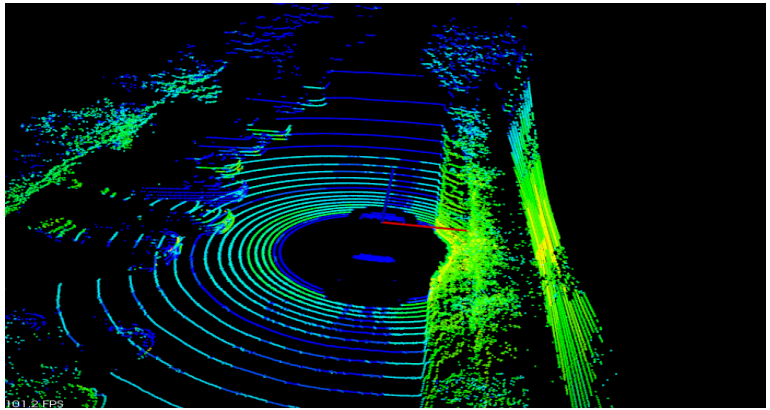
Velodyne HDL-64E LIDAR



$80000!

Limitations

Velodyne HDL-64E LIDAR



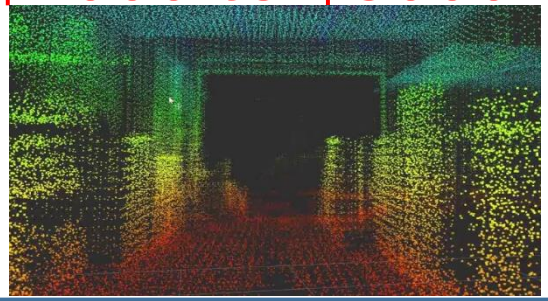
$80000!

Sparse and incomplete point cloud

Limitations

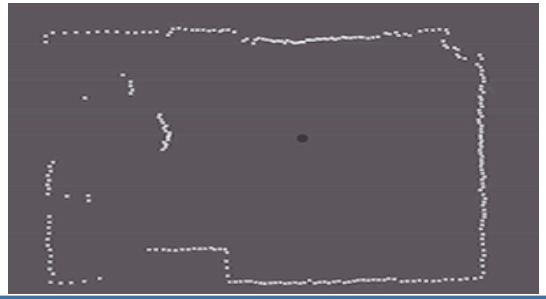
3D Lidar

$4000 to $5000



2D Lidar

$850 to $2500



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Contribution

- Propose a deep neural network jointly leveraging a single-beam LIDAR and a camera to estimate high-precision depth at a low cost.

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- Build a calibration system between the single beam LIDAR and a digital camera to provide a theoretical and practical basis to match the line point from LIDAR with the corresponding image pixels.

Contribution

- Propose a deep neural network jointly leveraging a single-beam LIDAR and a camera to estimate high-precision depth at a low cost.

- Build a calibration system between the single beam LIDAR and a digital camera to provide a theoretical and practical basis to match the line point from LIDAR with the corresponding image pixels.

- Apply a MLP network to online estimate the correct scale for the depth value in the image, realizing the purpose of extending single-beam LIDAR to full resolution.

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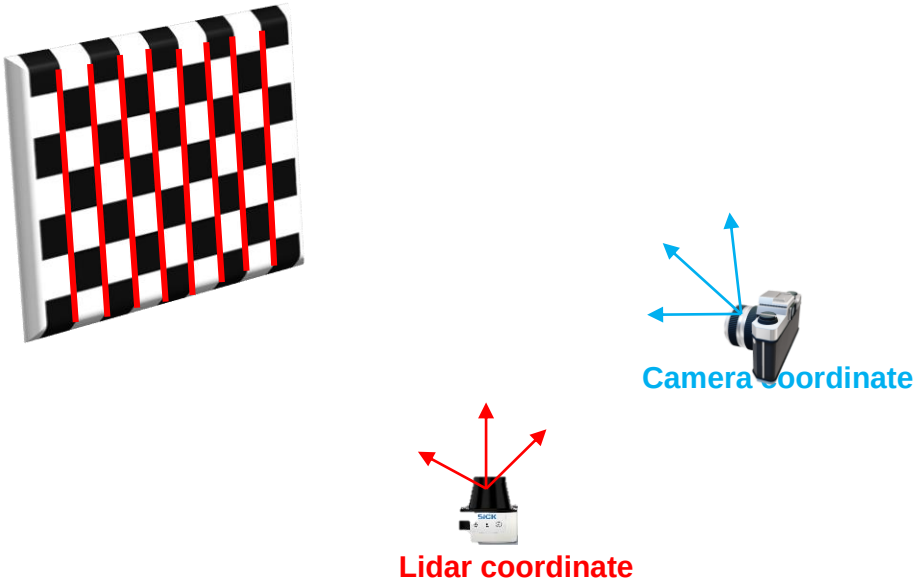
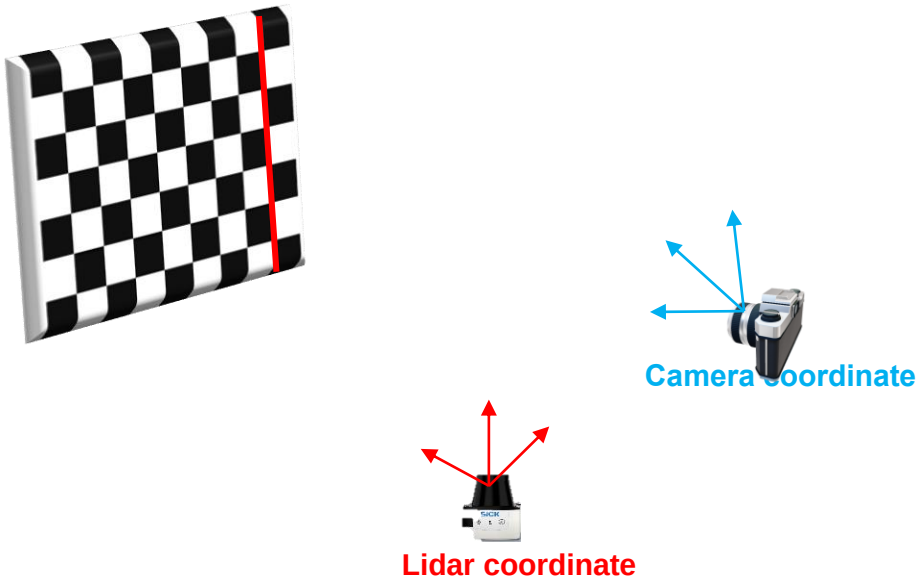
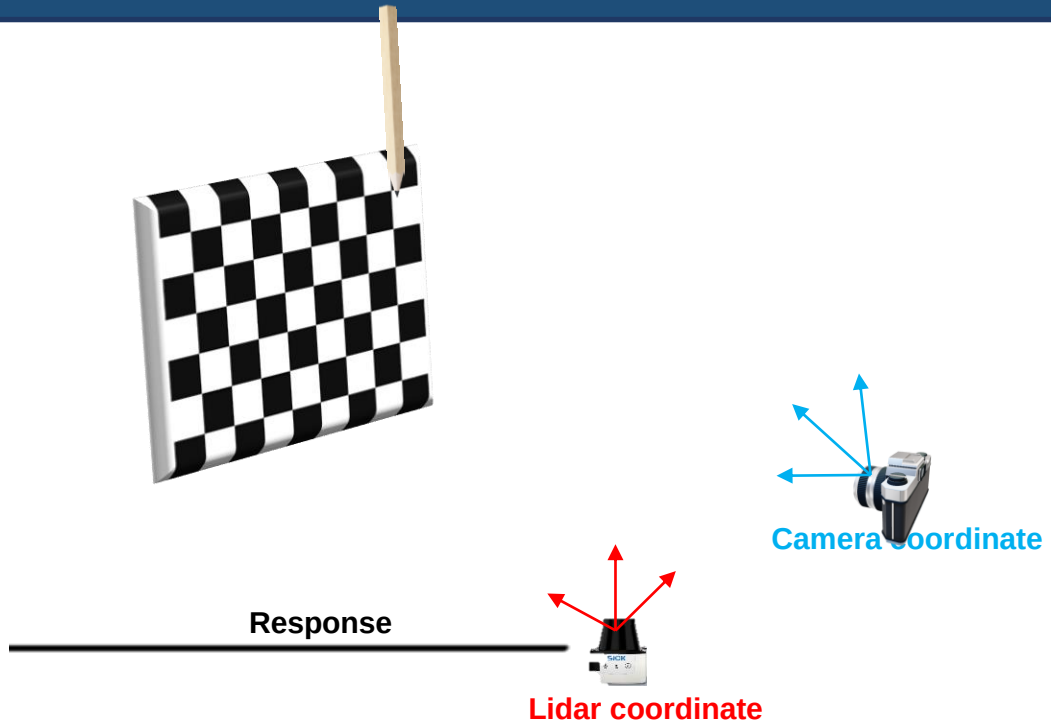
2D Lidar-Camera Calibration



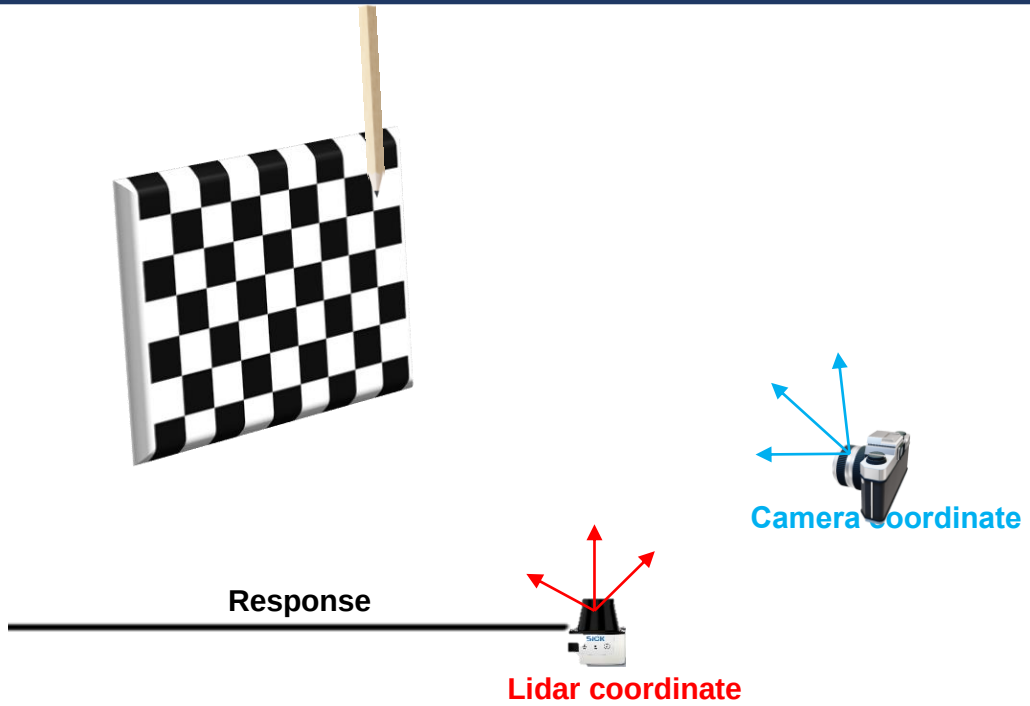
2D Lidar-Camera Calibration



2D Lidar-Camera Calibration



2D Lidar-Camera Calibration



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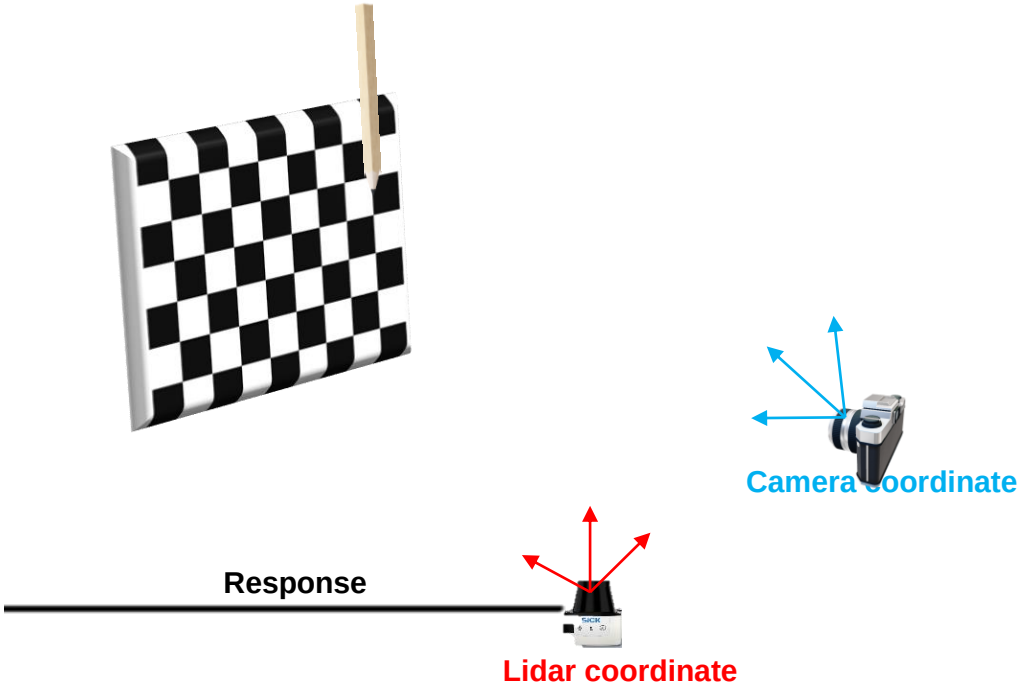

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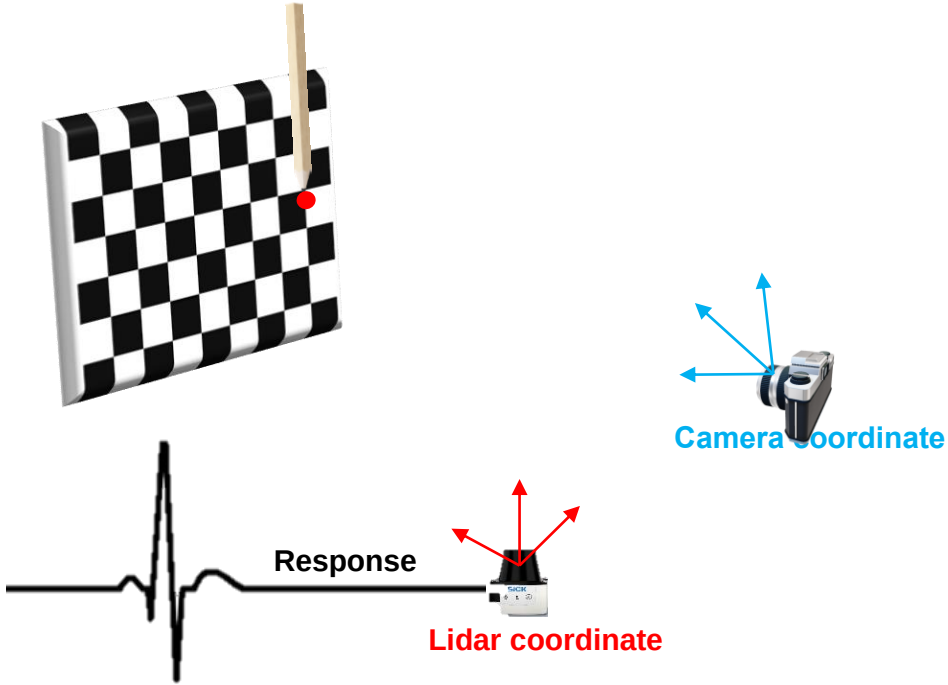

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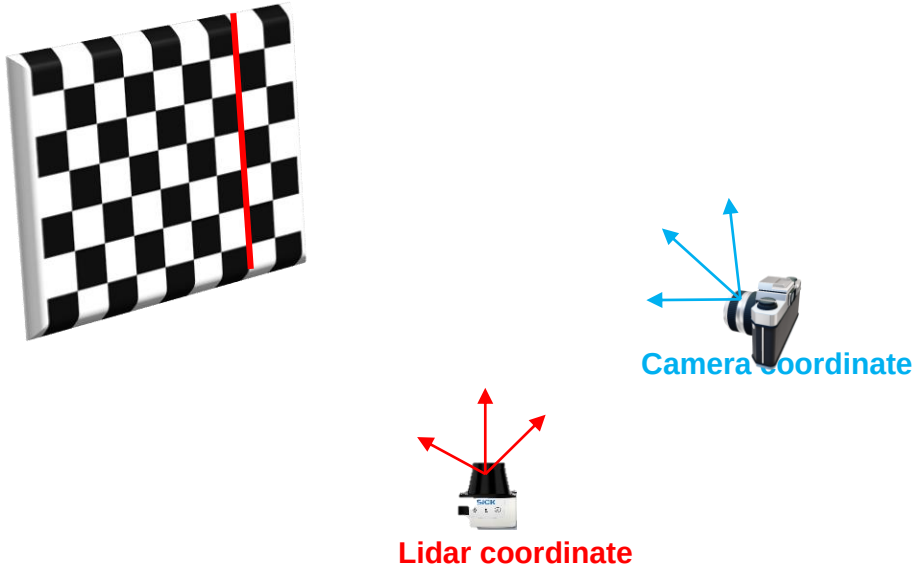

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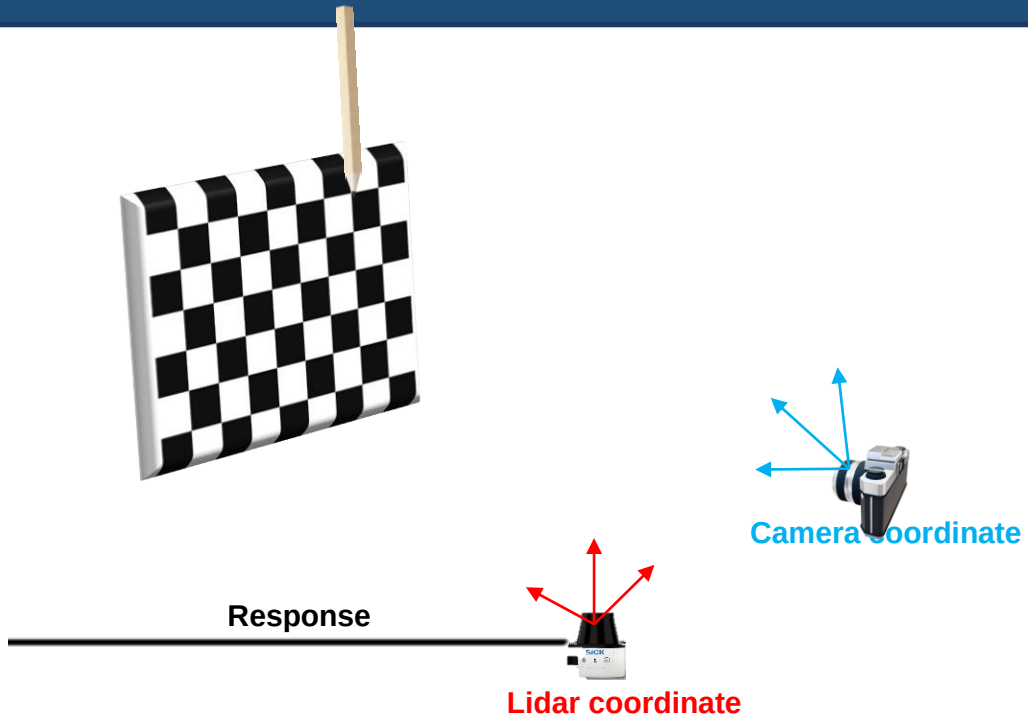

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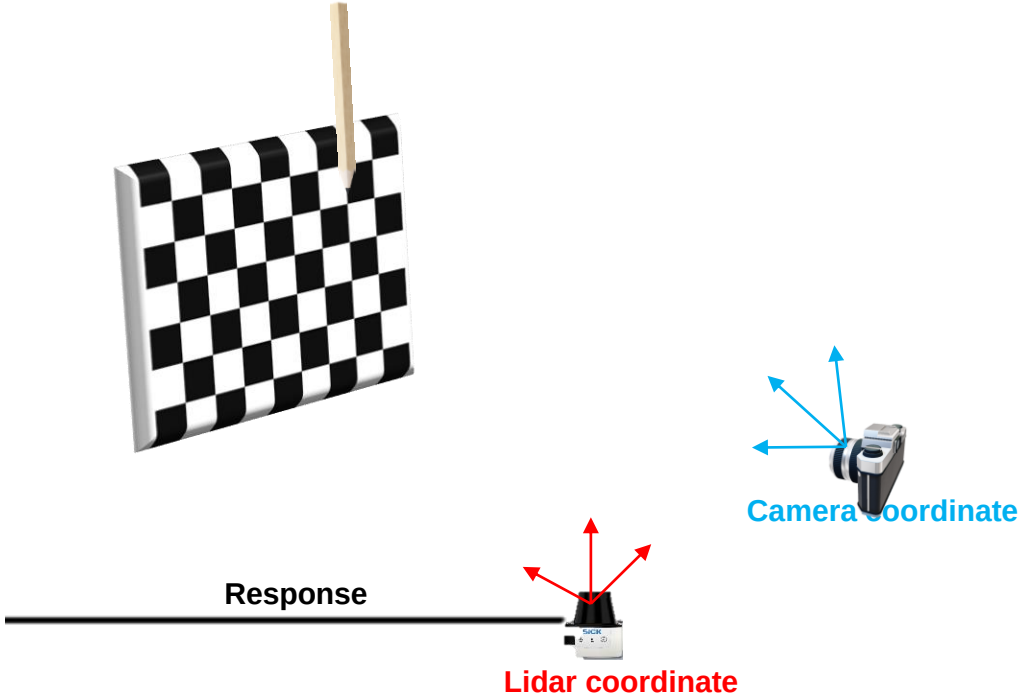

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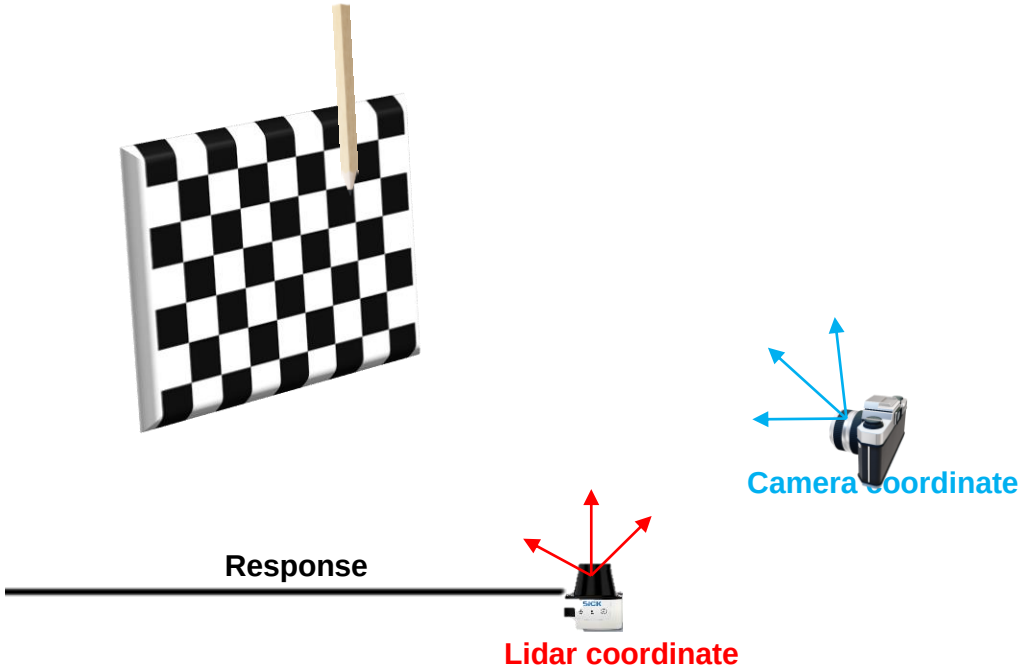

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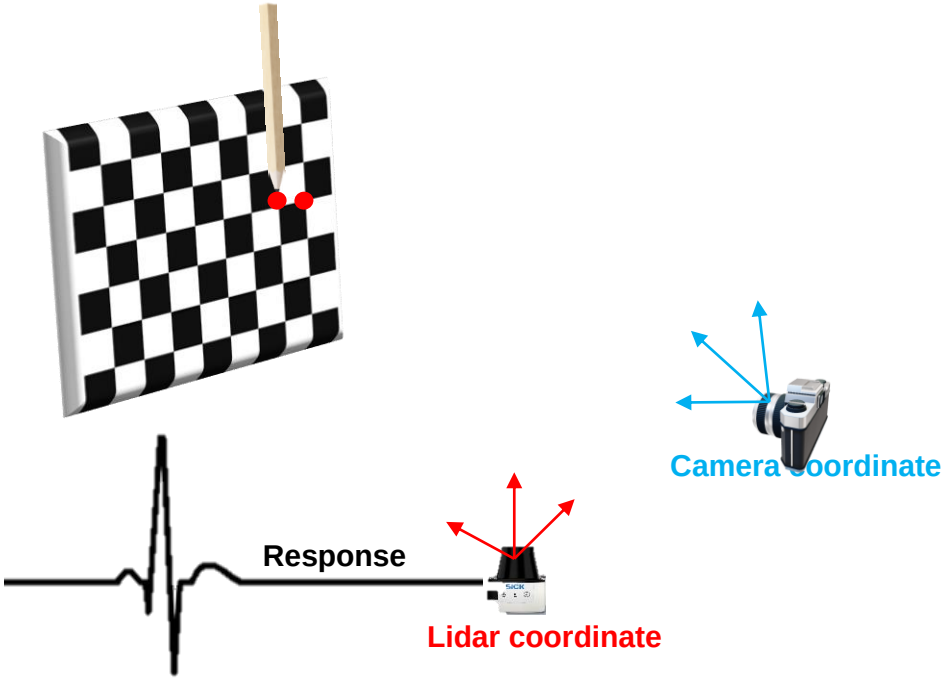

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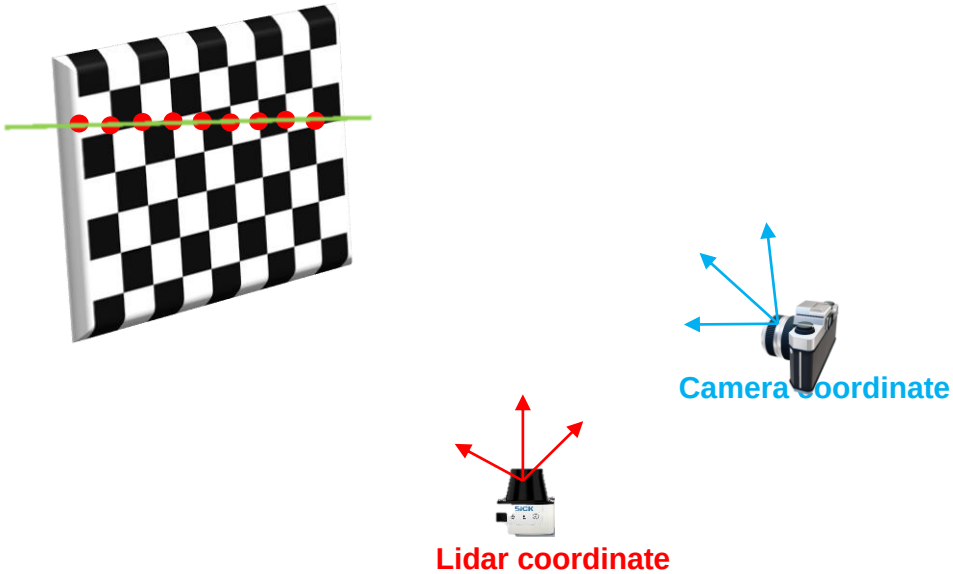

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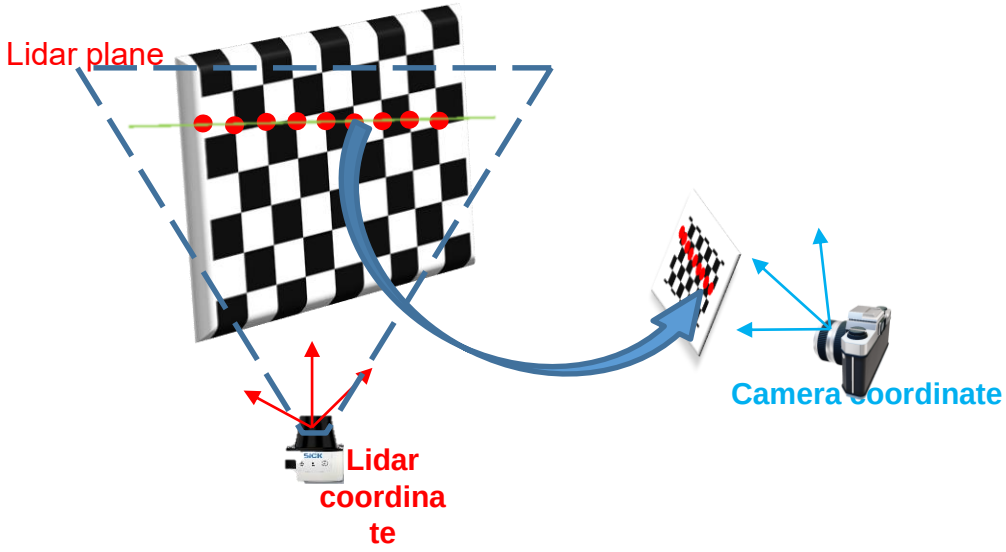
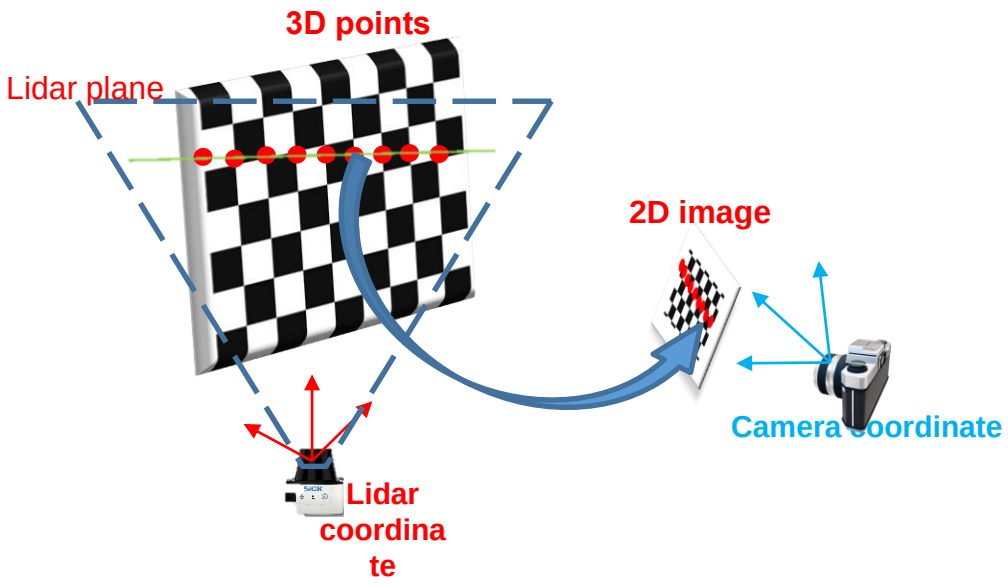


2D Lidar-Camera Calibration

3D-2D correspondences



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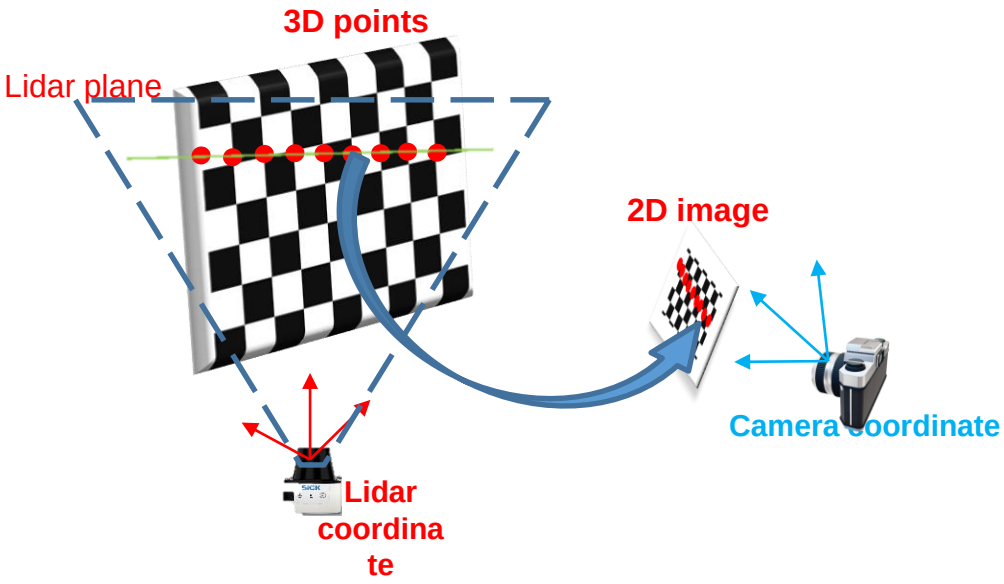

3D-2D correspondences

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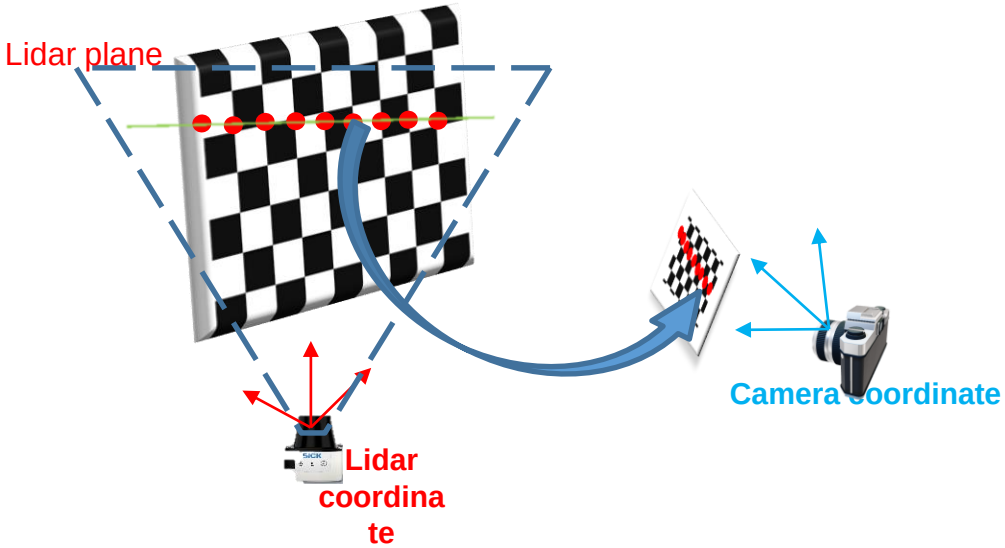
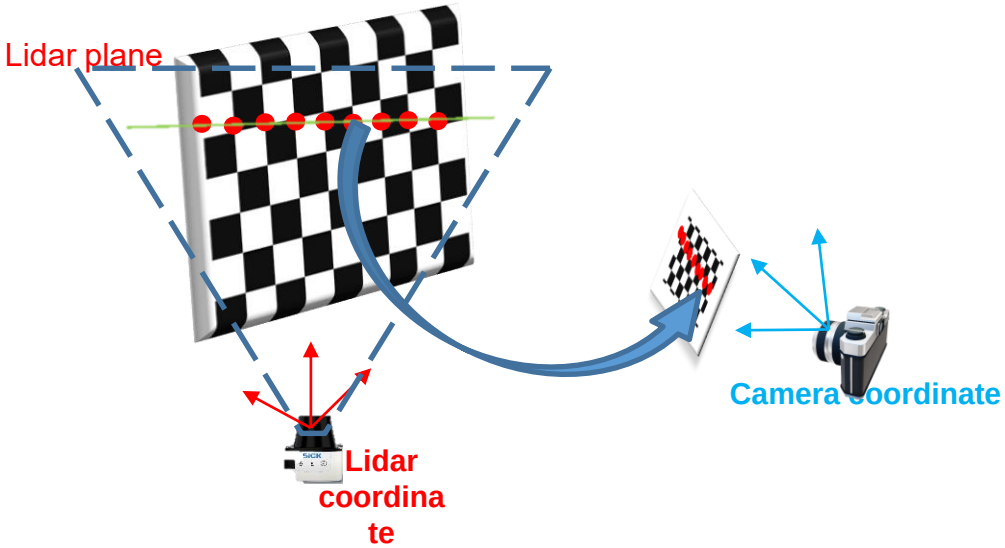


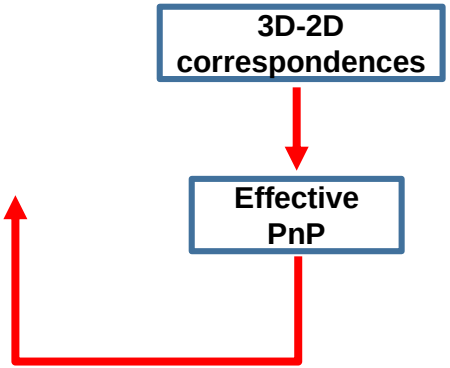
3D-2D correspondences

↓

Effective PnP

2D Lidar-Camera Calibration





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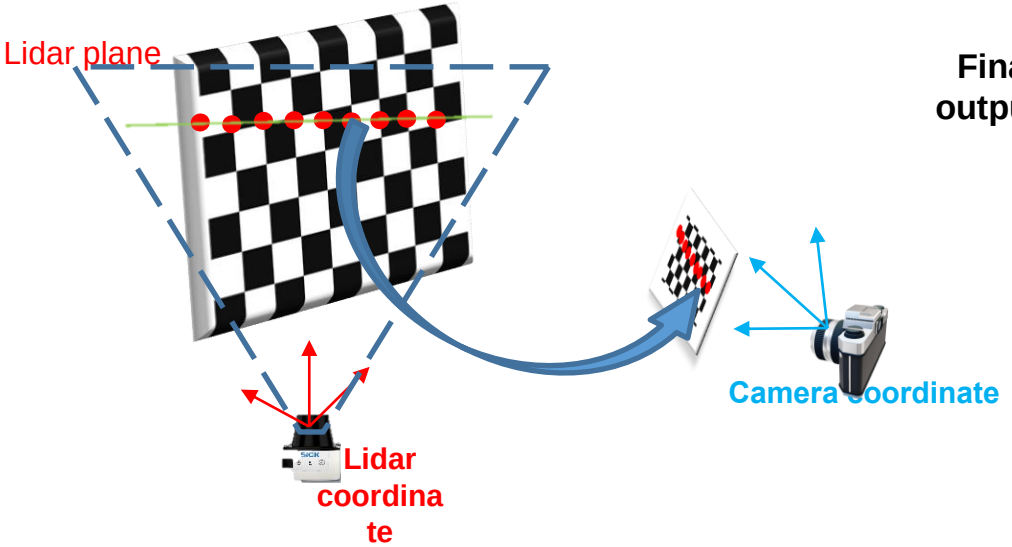

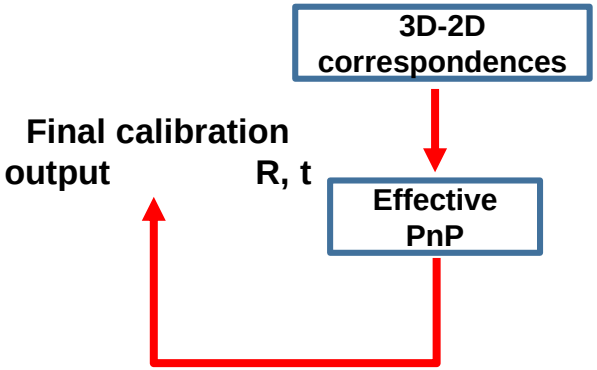

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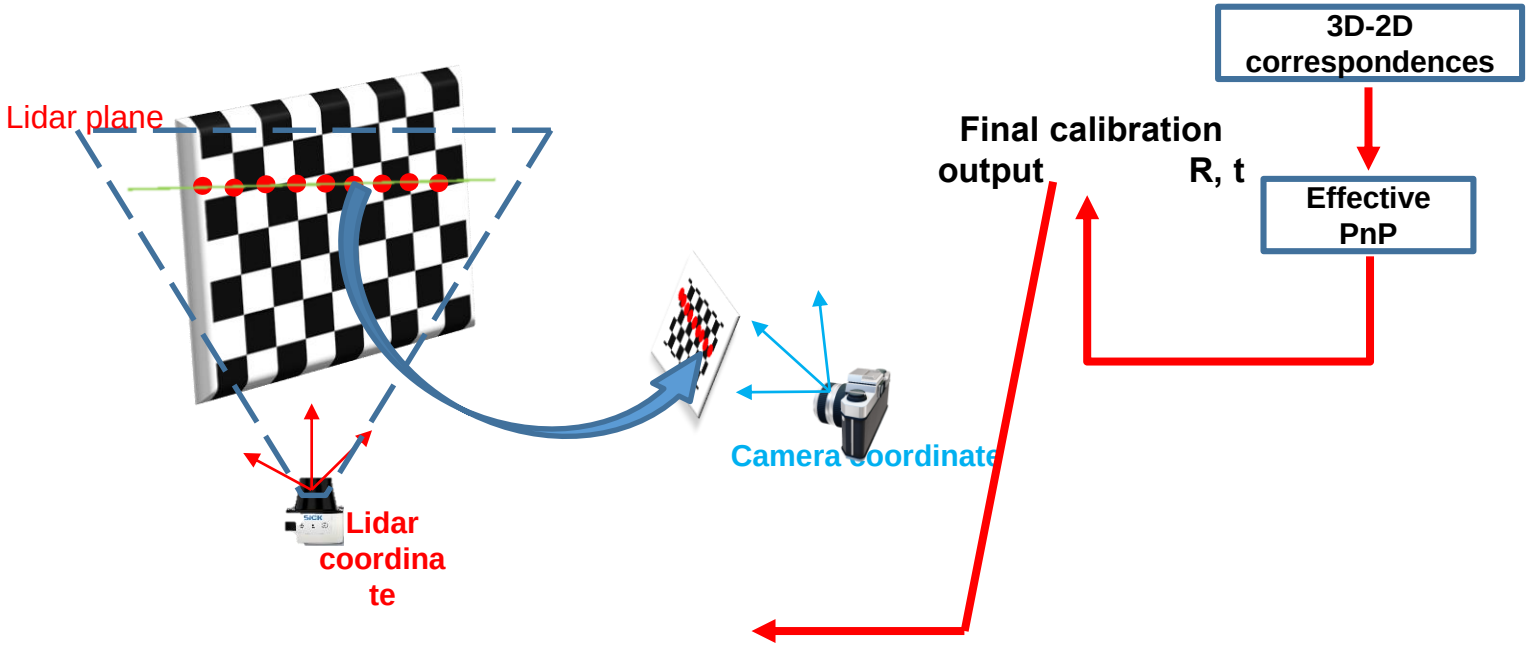

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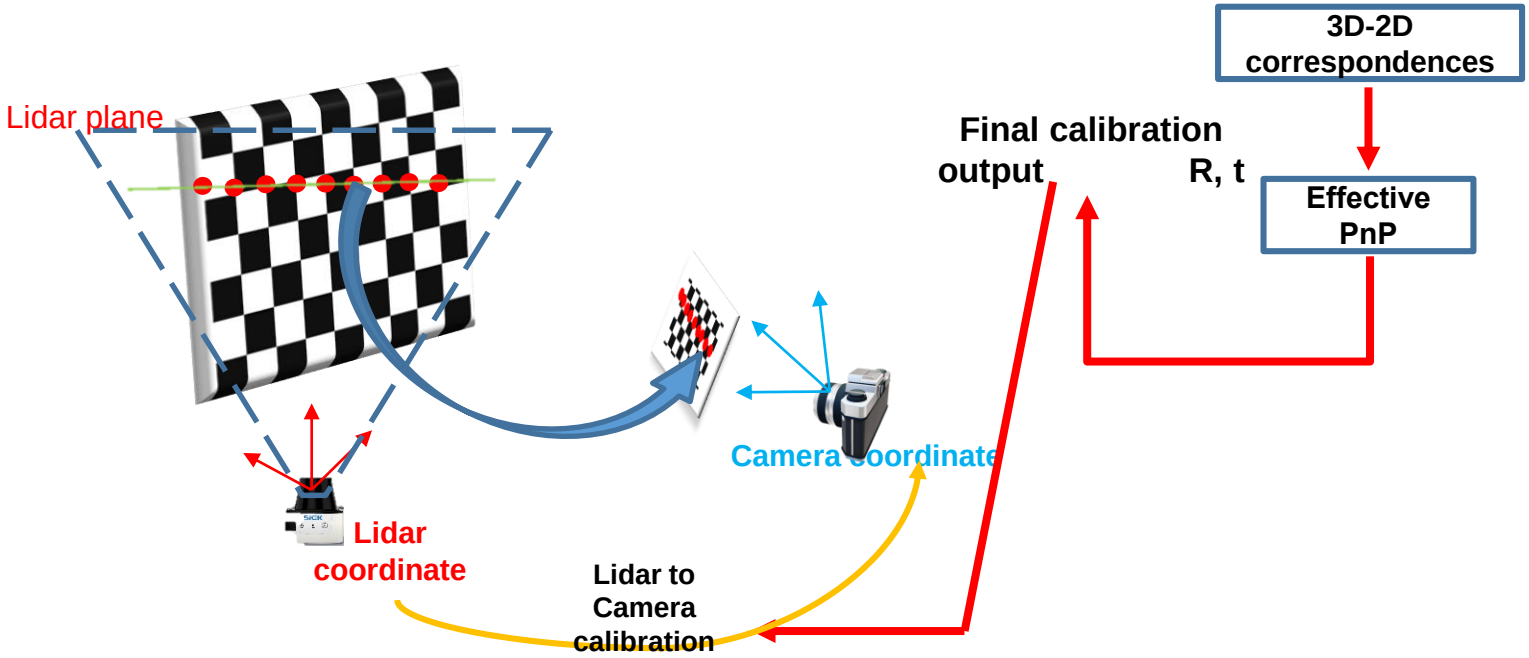
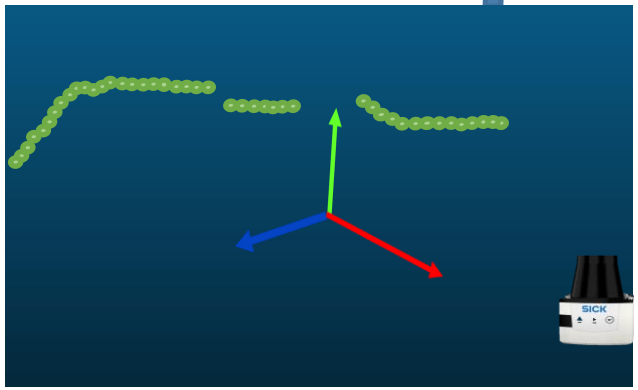
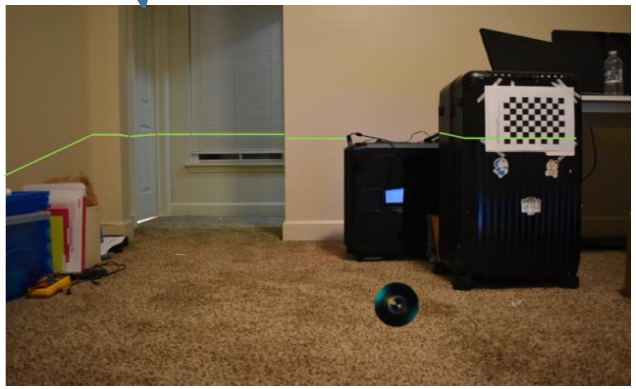


2D Lidar-Camera Calibration

Final calibration output R, t



3D points



Corresponding 2D pixels

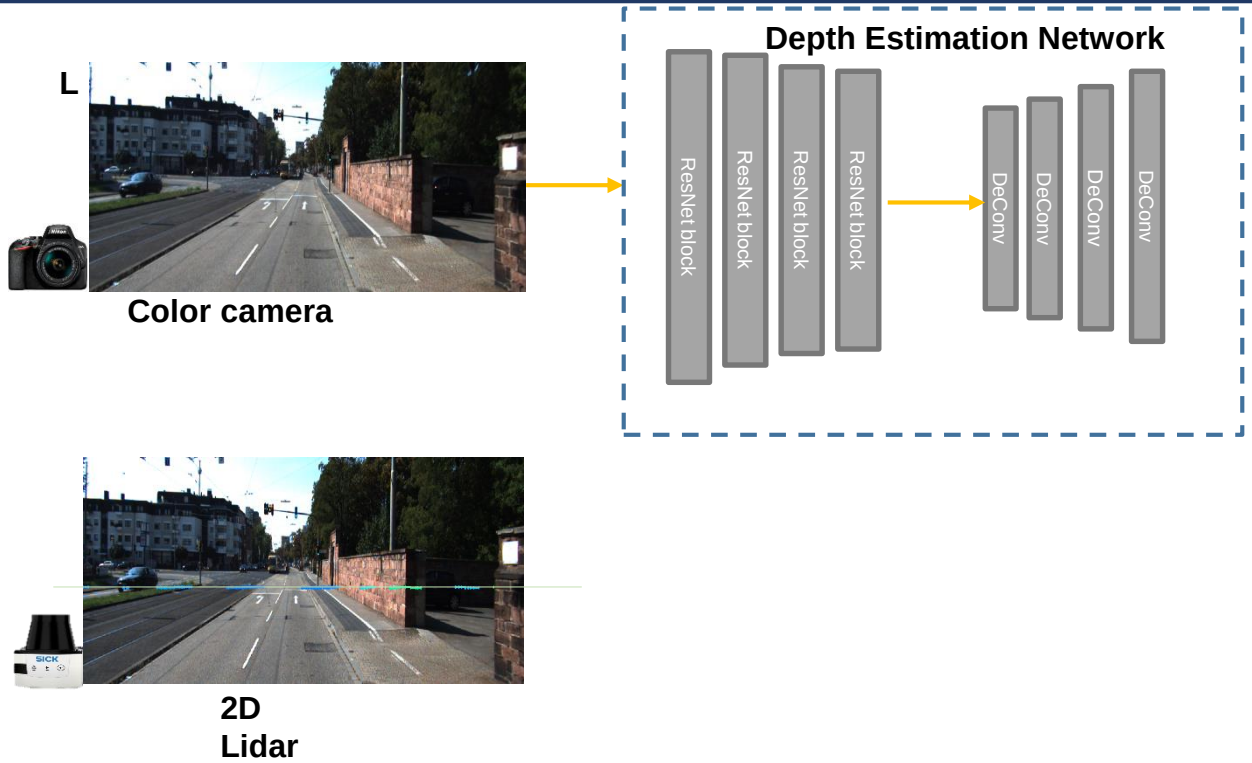
Self-supervised depth estimation network

L

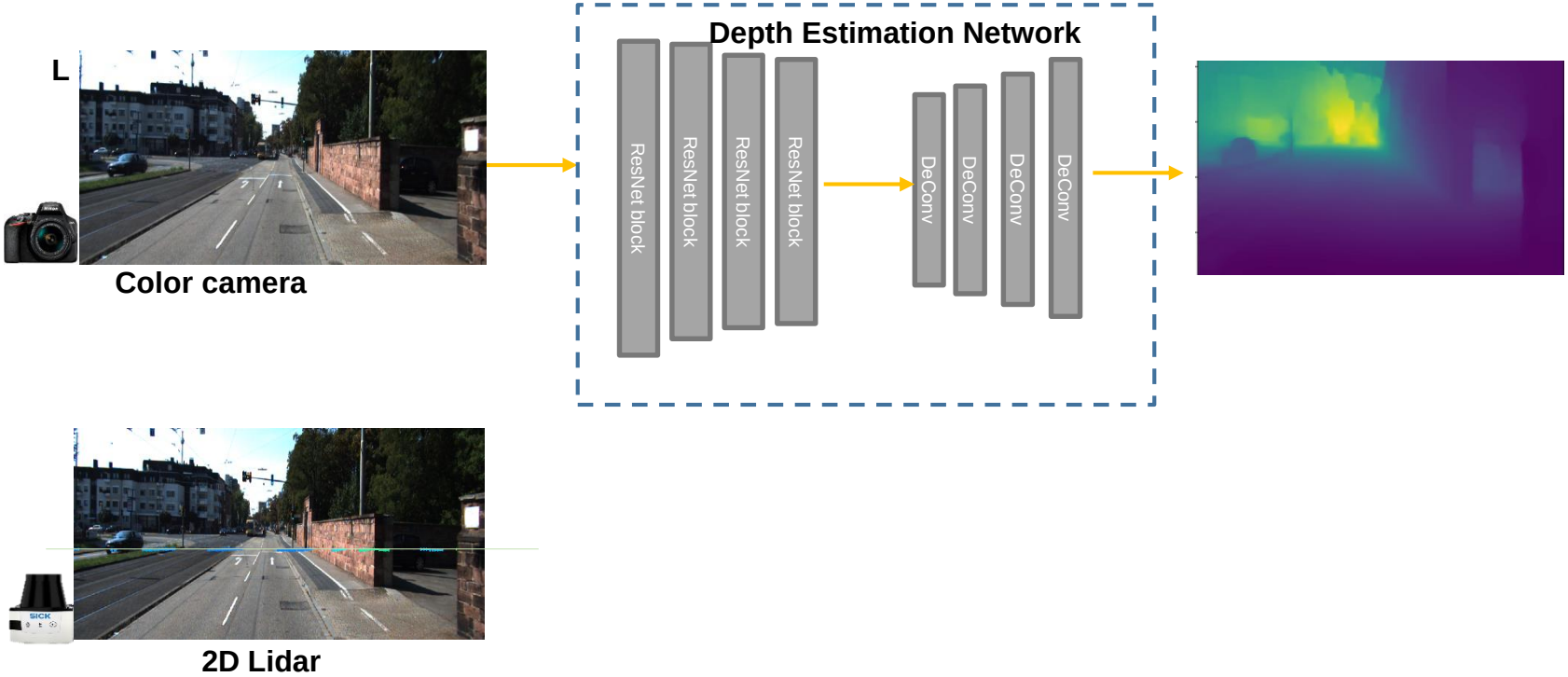
Color camera

2D
Lidar

Self-supervised depth estimation network



Self-supervised depth estimation network



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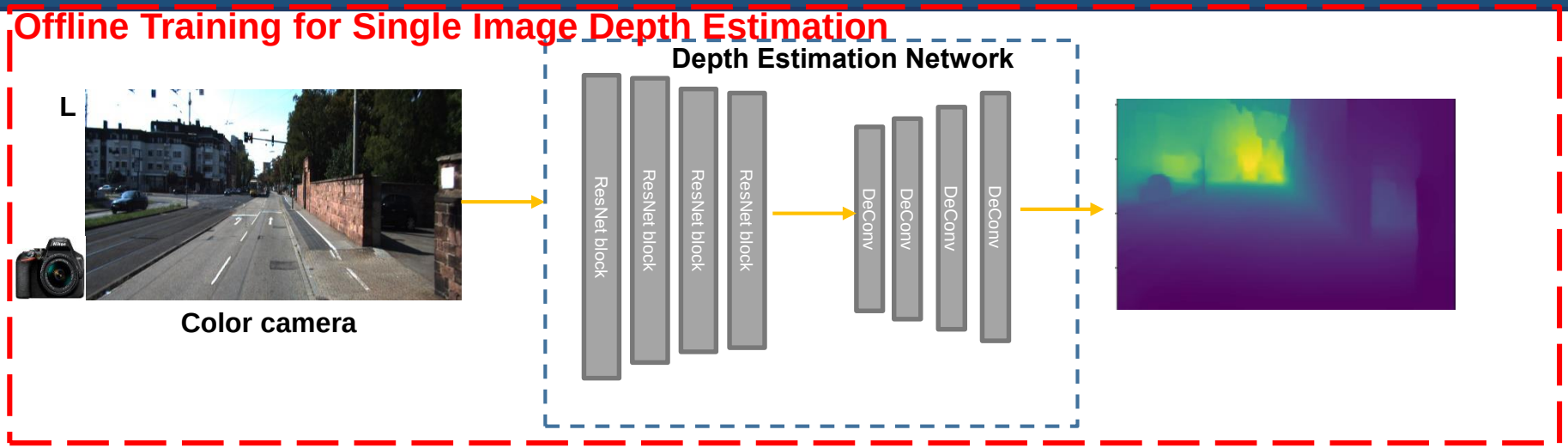
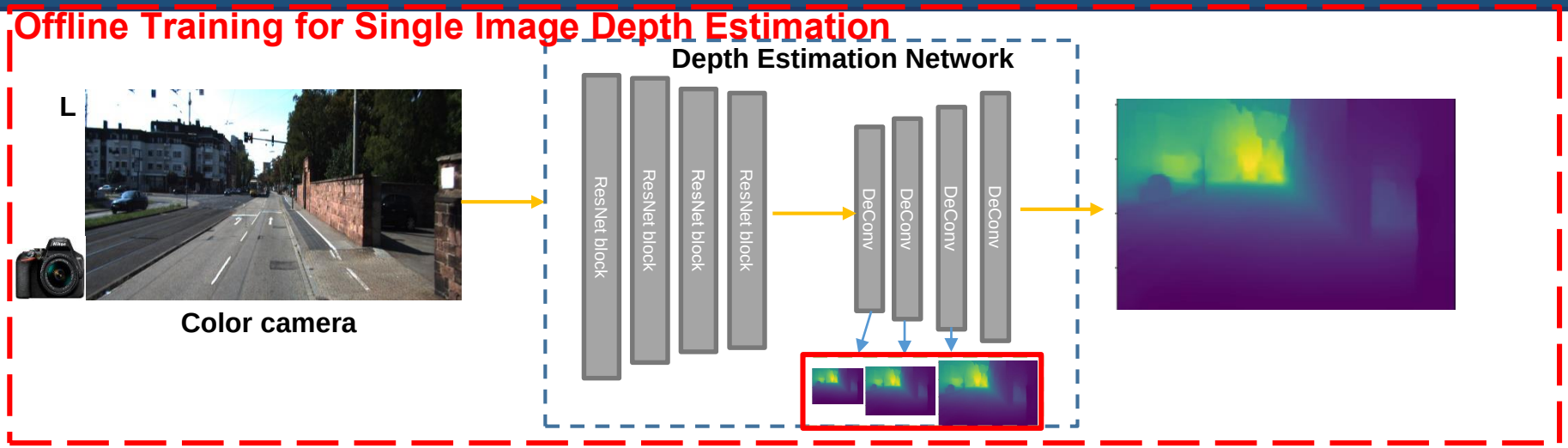


2D Lidar

Self-supervised depth estimation network



2D Lidar

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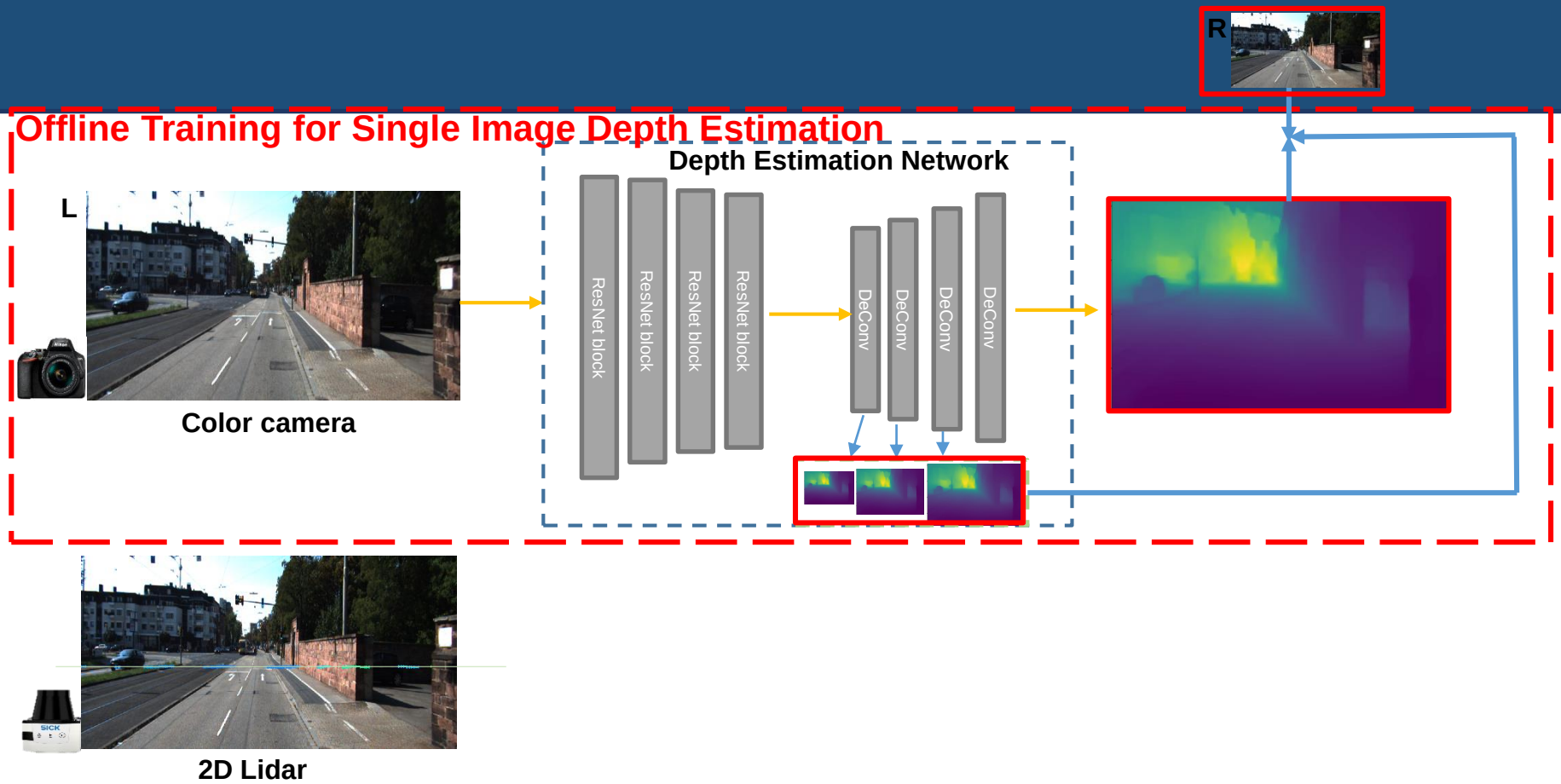
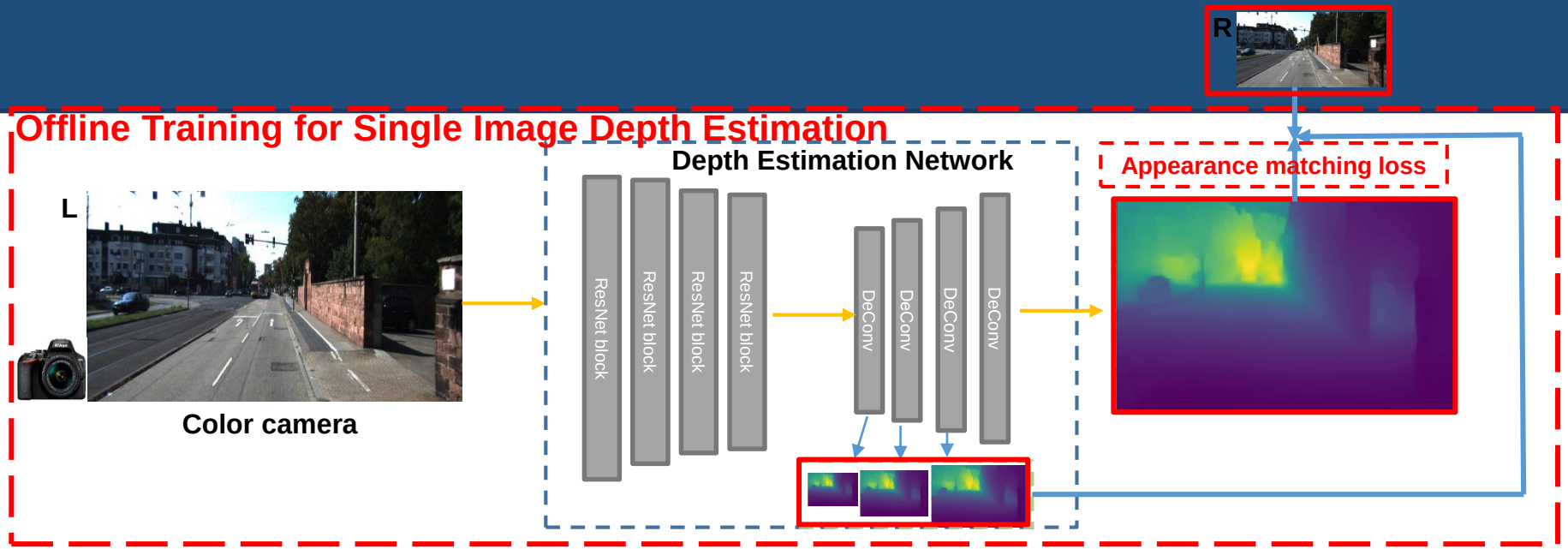
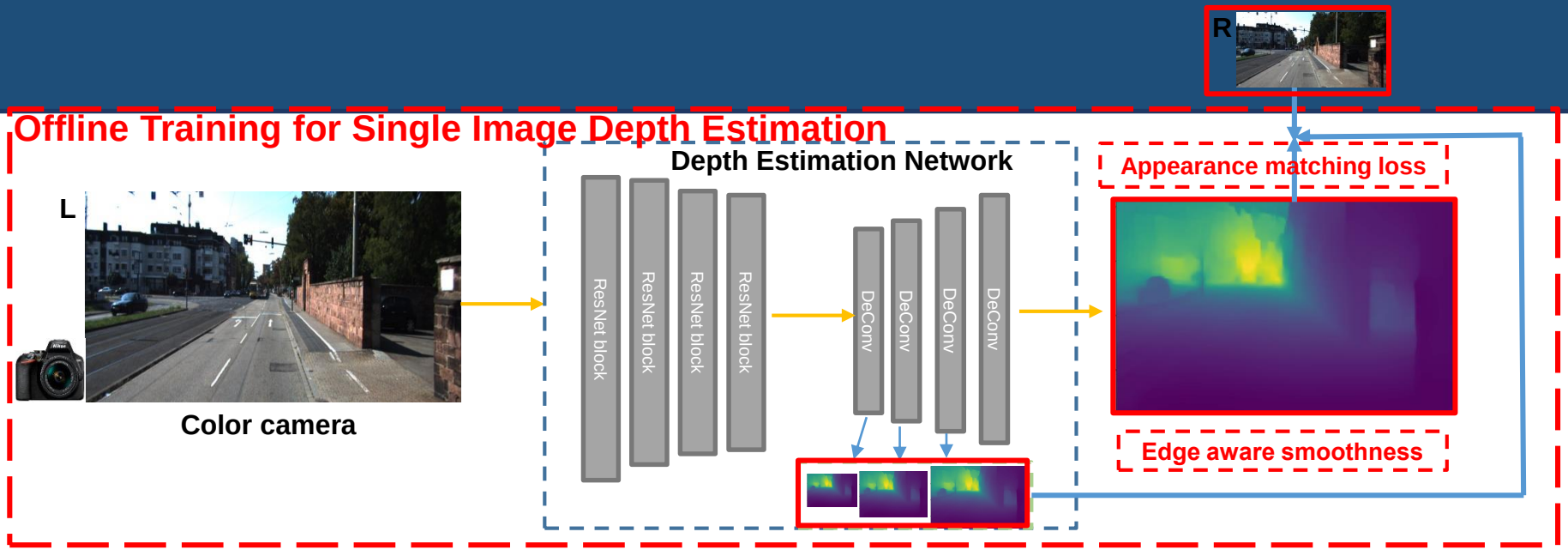


Self-supervised depth estimation network



2D Lidar

Self-supervised depth estimation network

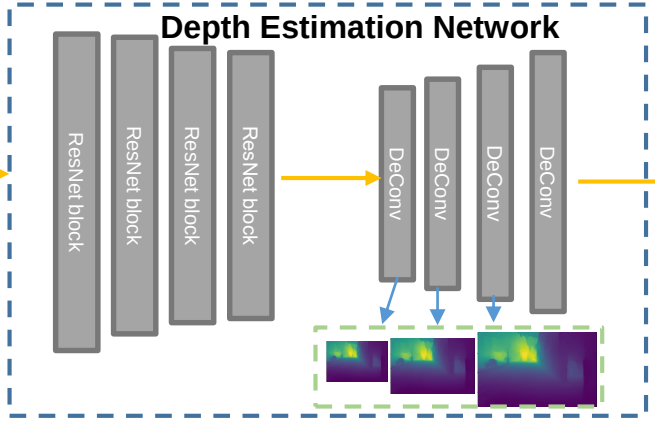


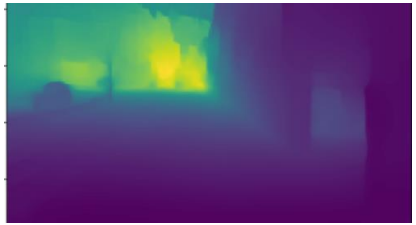
Self-supervised depth estimation network

In real application

Only one image is needed!

Color camera





2D Lidar

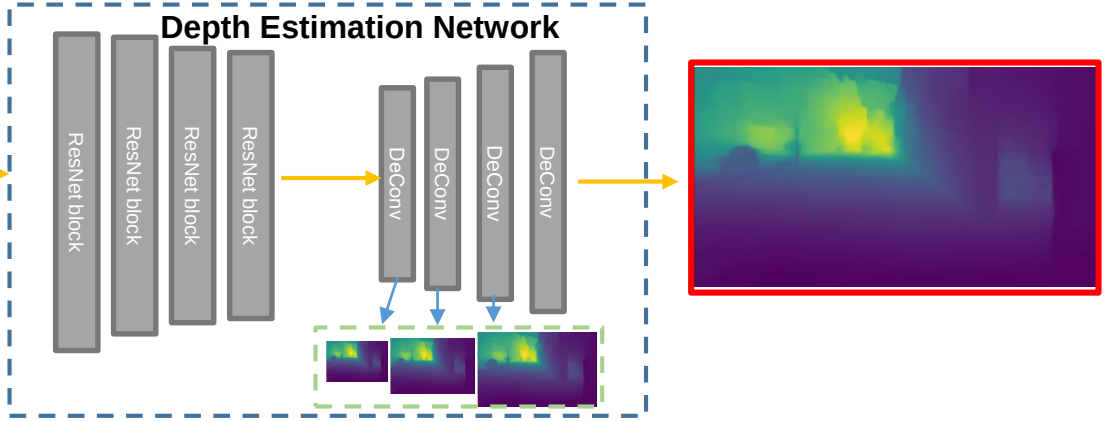
Self-supervised depth estimation network

In real application

Only one image is needed!

L

Color camera



2D
Lidar

Constraints for Self-supervised depth estimation

We enforce the reconstructed thermal images $\tilde{I}_{new}$ to be the same as the original thermal images I_{new} at the corresponding pixels as appearance matching loss $\boldsymbol{L_{match}}$:

$$L_{match} = \frac{1}{N}\sum_{ij}\frac{\alpha}{2}(1 - SSIM(I_{newij}, \tilde{I}_{newij})) + (1-\alpha)e^{\beta\nabla(I)}(||I_{newij} - \tilde{I}_{newij}||_1)$$

Edge-aware smoothness loss $\boldsymbol{L_{smooth}}$ utilize estimated depth *D*, Laplacian of Gaussian *G* and color image I_{new} to penalize depth discontinuities in flat regions and allow depth changes at object boundaries:

$$L_{smooth} = w\left\|\frac{|\nabla^2(D \otimes G)|}{\|\nabla I_{new}\|}\right\|_1 \times \frac{1}{\|D\|}$$

Online depth refinement

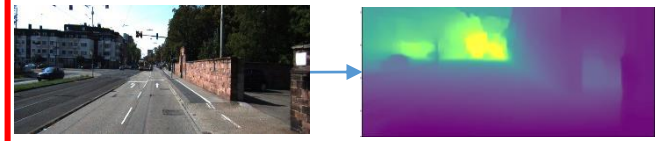
Online Depth Adjusting Based on Lidar

2D Lidar

Corresponding pixels on the images

Online depth refinement

Online Depth Adjusting Based on Lidar

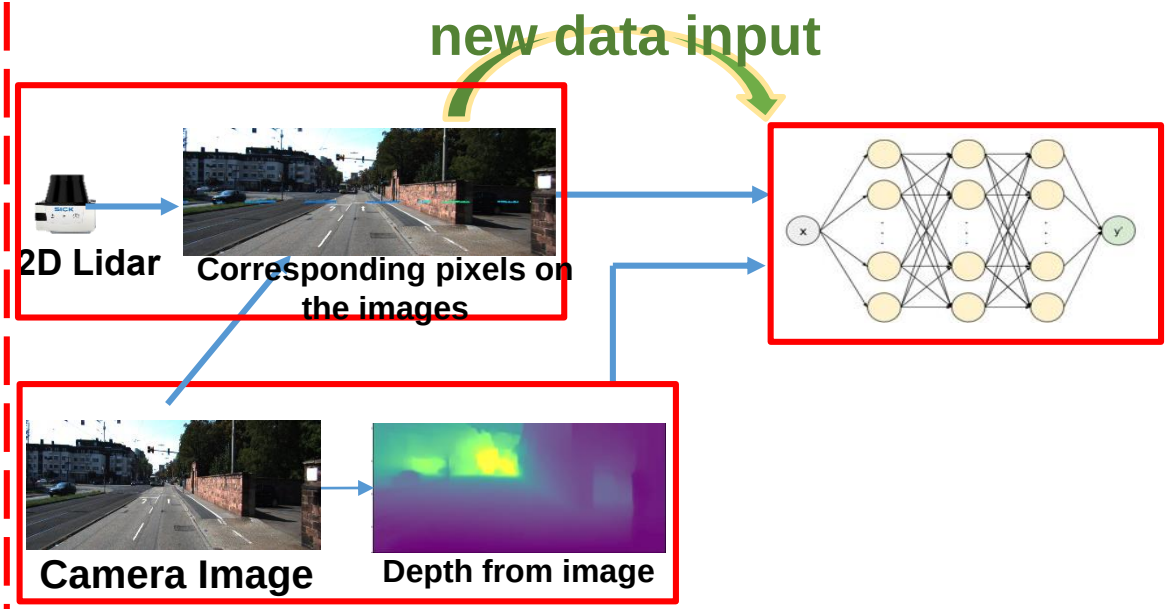


Camera Image

Depth from image

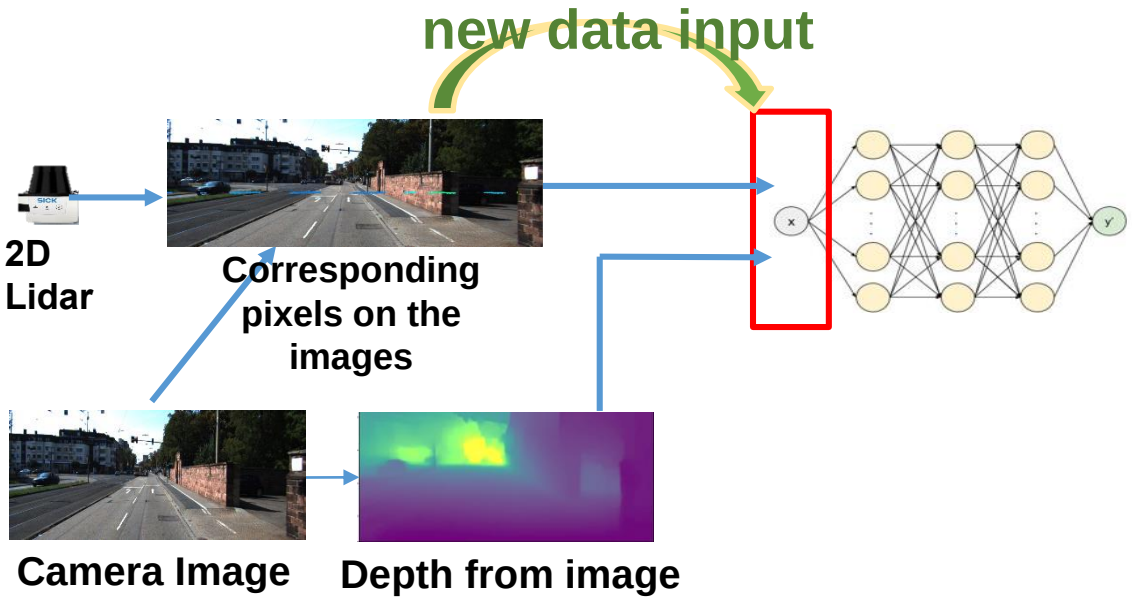
Online depth refinement

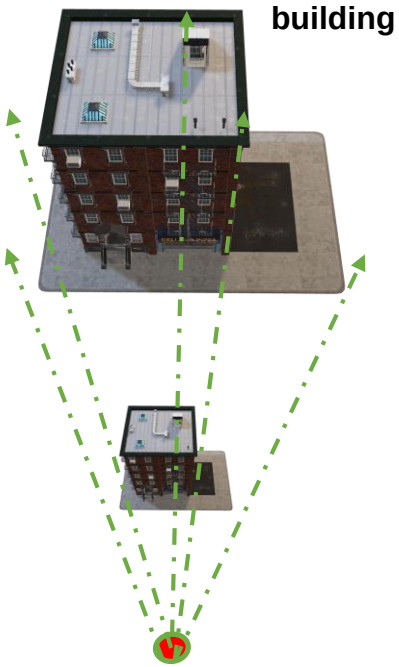
Online Depth Adjusting Based on Lidar



Online depth refinement

Online Depth Adjusting Based on Lidar





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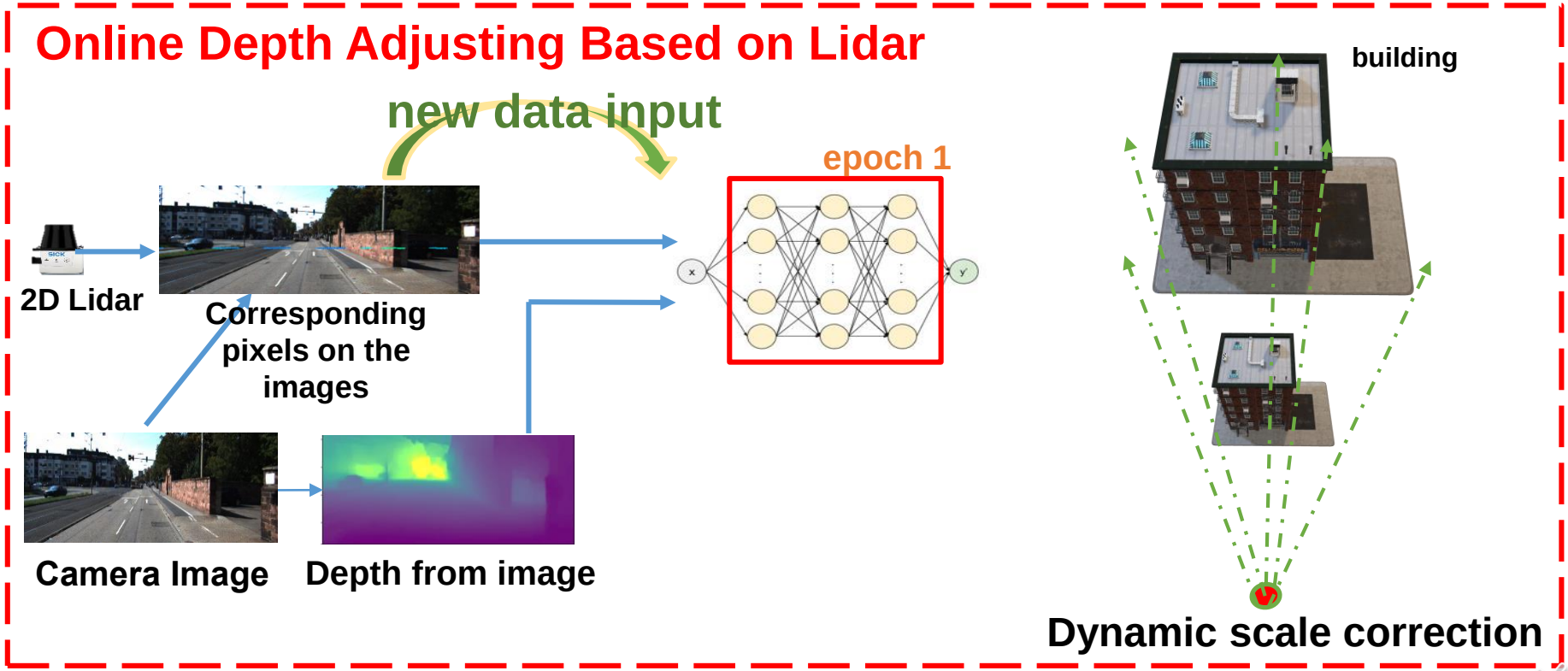
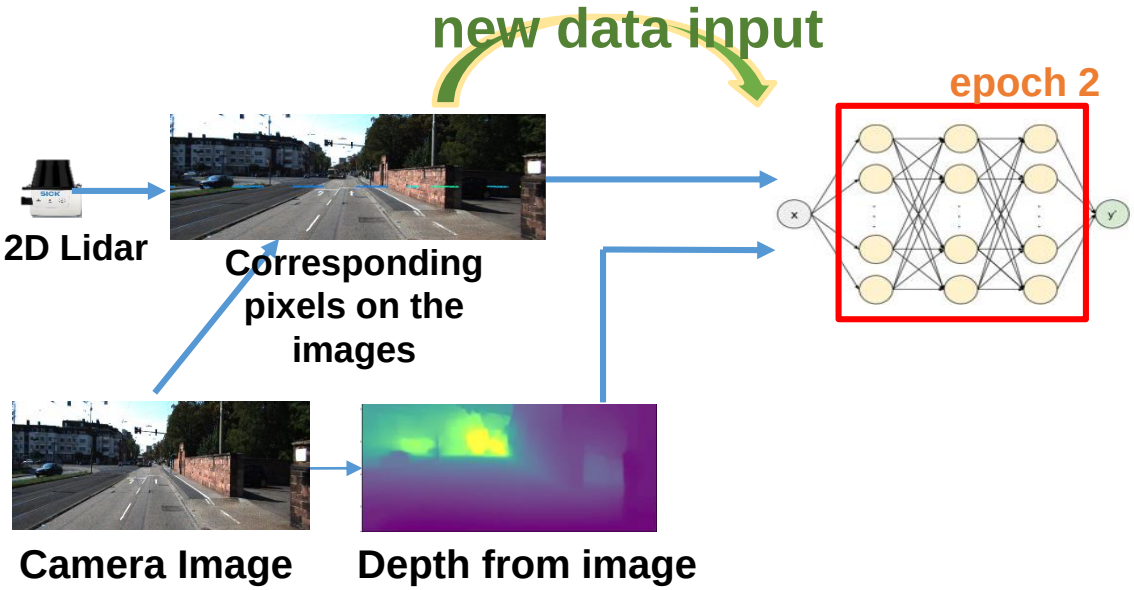
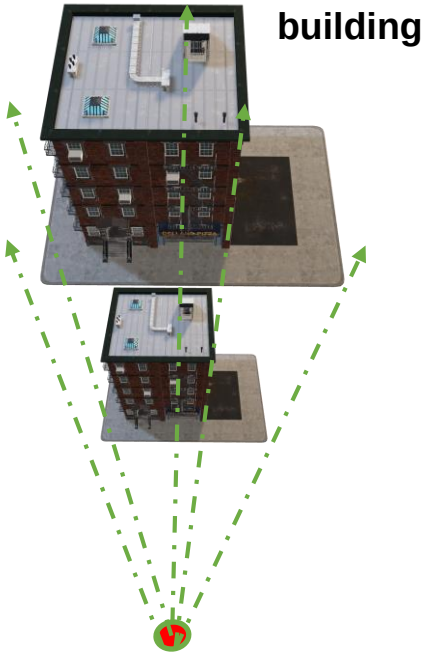


Online depth refinement

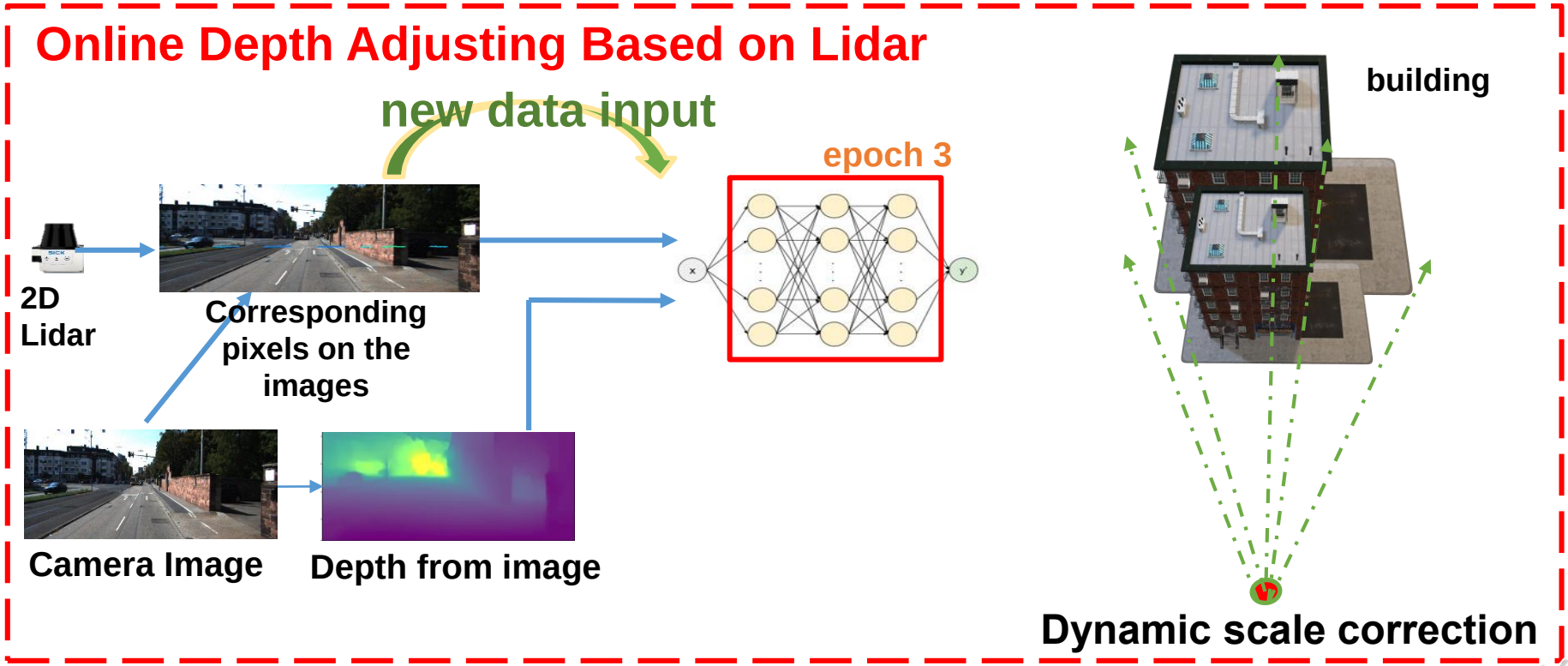
Online Depth Adjusting Based on Lidar



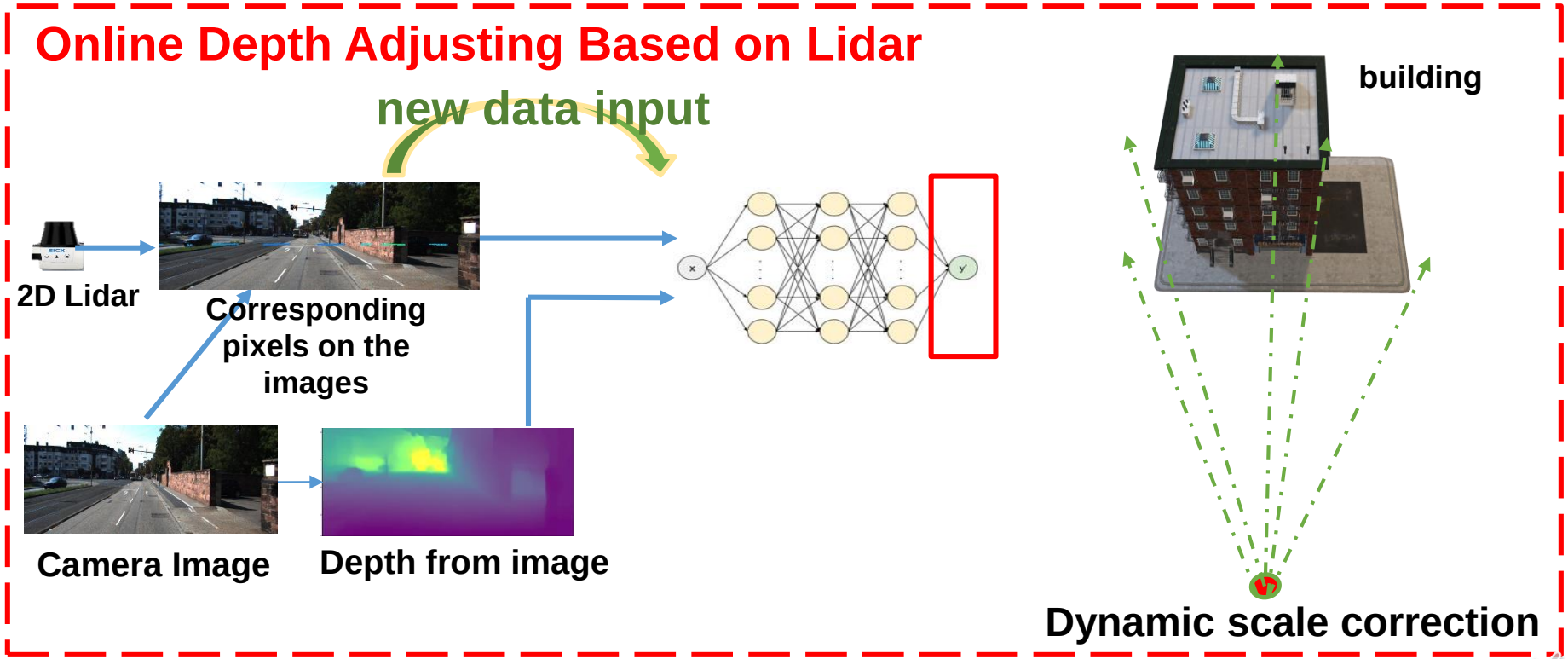


Dynamic scale correction

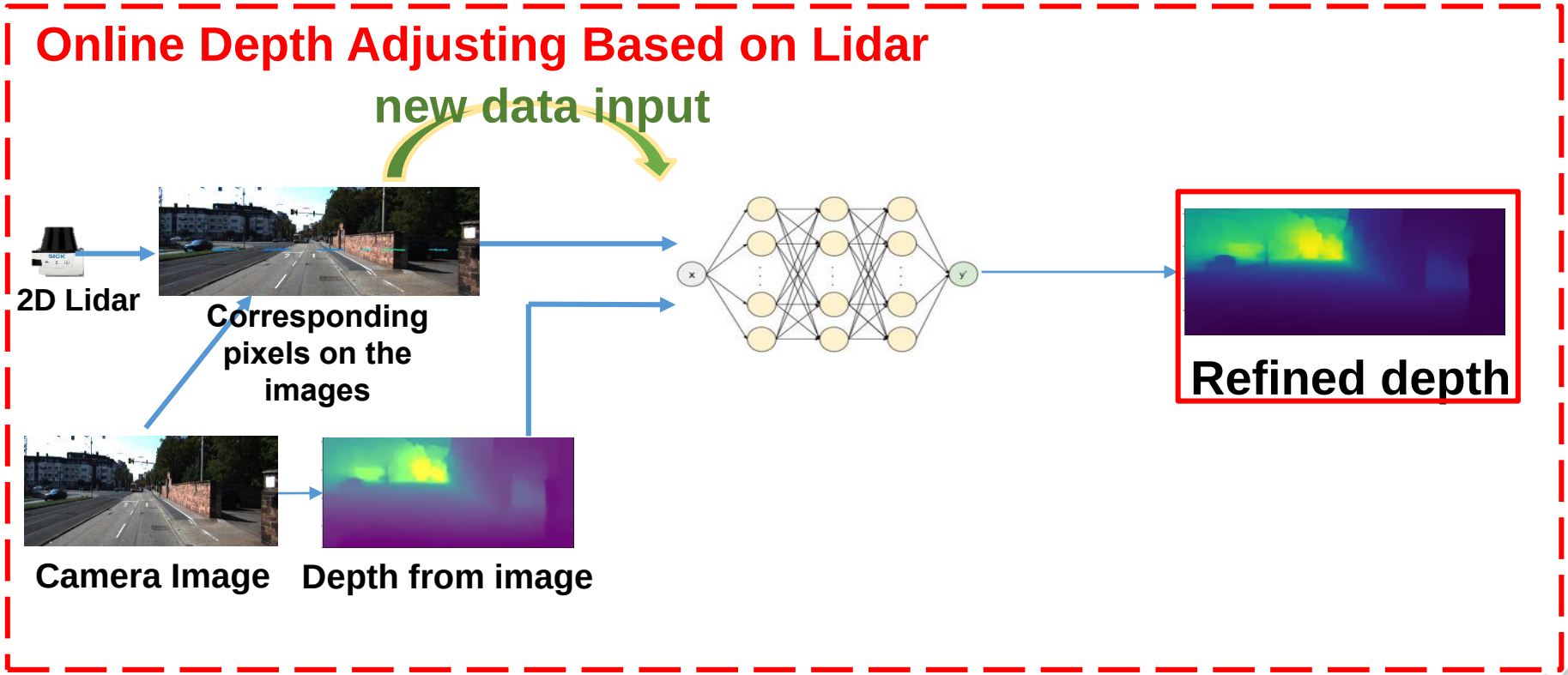
Online depth refinement



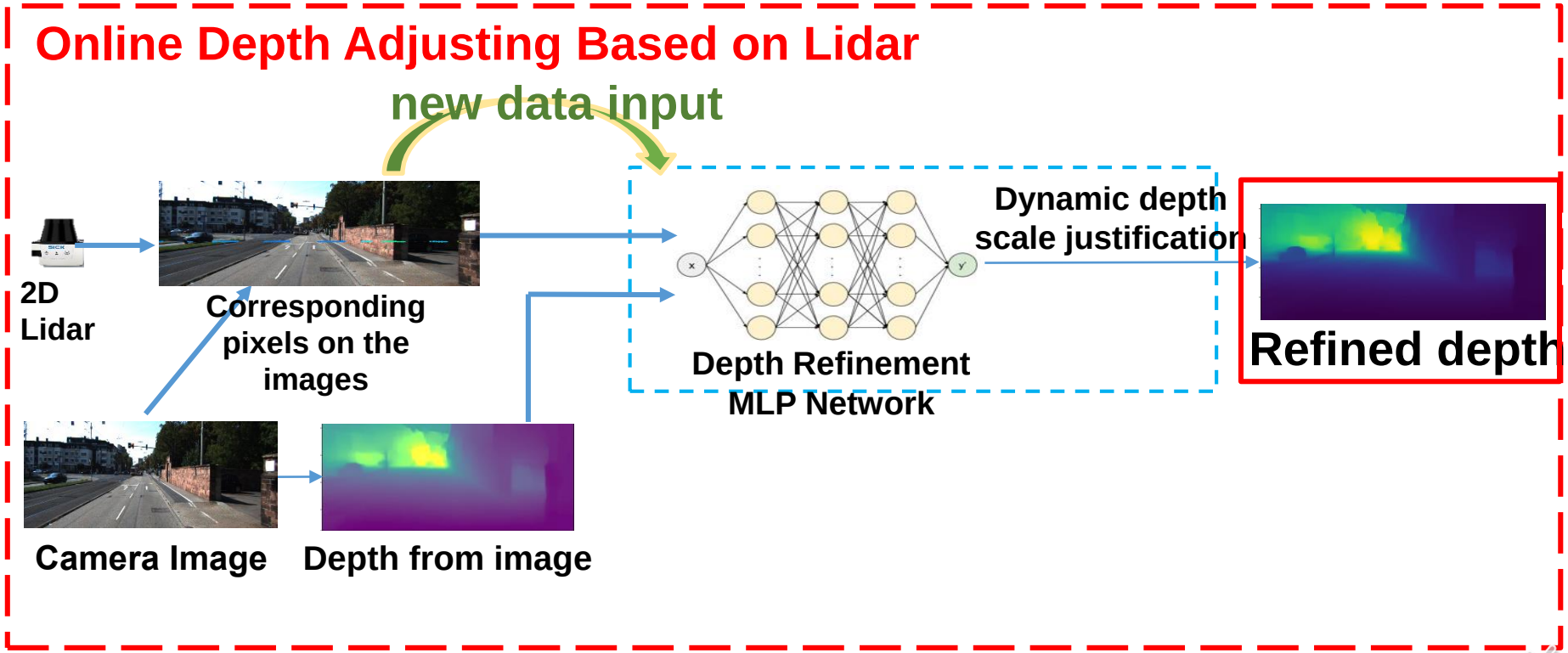
Online depth refinement



Online depth refinement



Online depth refinement



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Depth estimation result

RGB

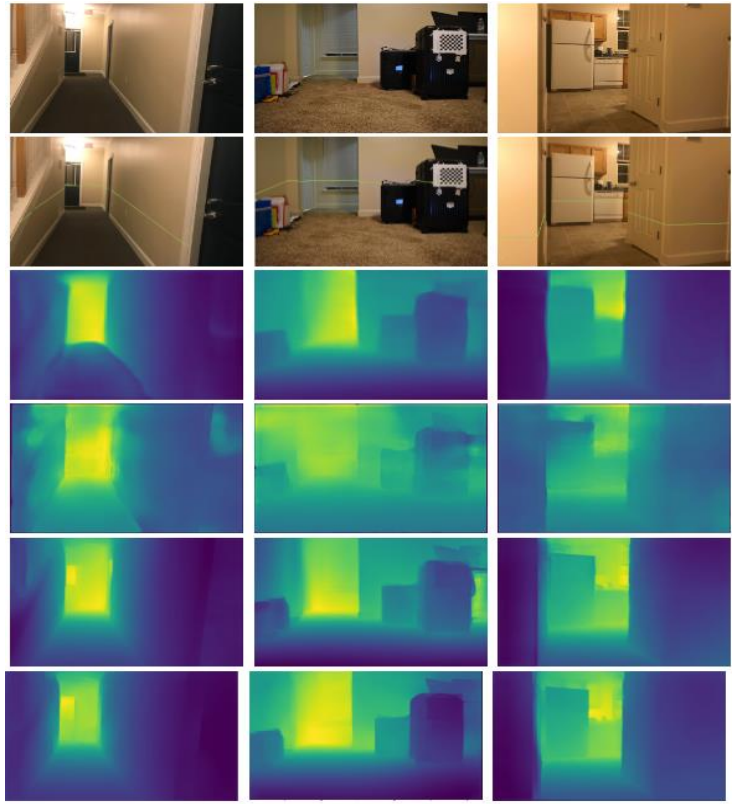
Lidar

[1]

[2]

[3]

Ours



[1] Iro Laina, Christian Rupprecht, Vasileios Belagiannis, Federico Tombari, and Nassir Navab, “Deeper depth prediction with fully convolutional residual networks,” in 3DV, 2016.

[2] Xiaojuan Qi, Renjie Liao, Zhengzhe Liu, Raquel Urtasun, and Jiaya Jia,“Geonet: Geometric neural network for joint depth and surface normal estimation,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2018, pp. 283–291.

[3] Wei Yin, Yifan Liu, Chunhua Shen, and Youliang Yan, “Enforcing geometric constraints of virtual normal for depth prediction,”in Proceedings of the IEEE International Conference on Computer Vision,2019, pp. 5684–5693.

Depth estimation result

RGB

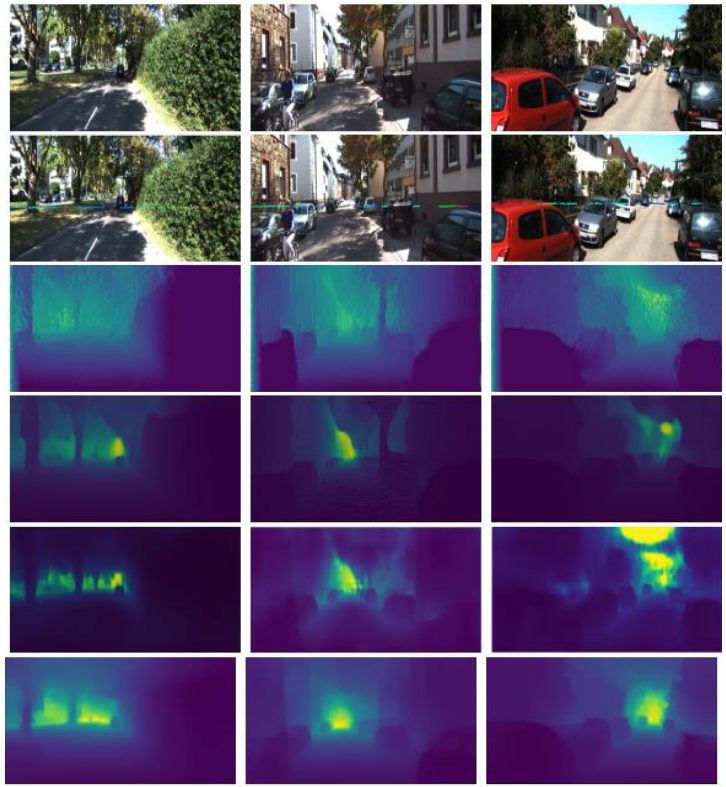
Lidar

[4]

[5]

[6]

Ours

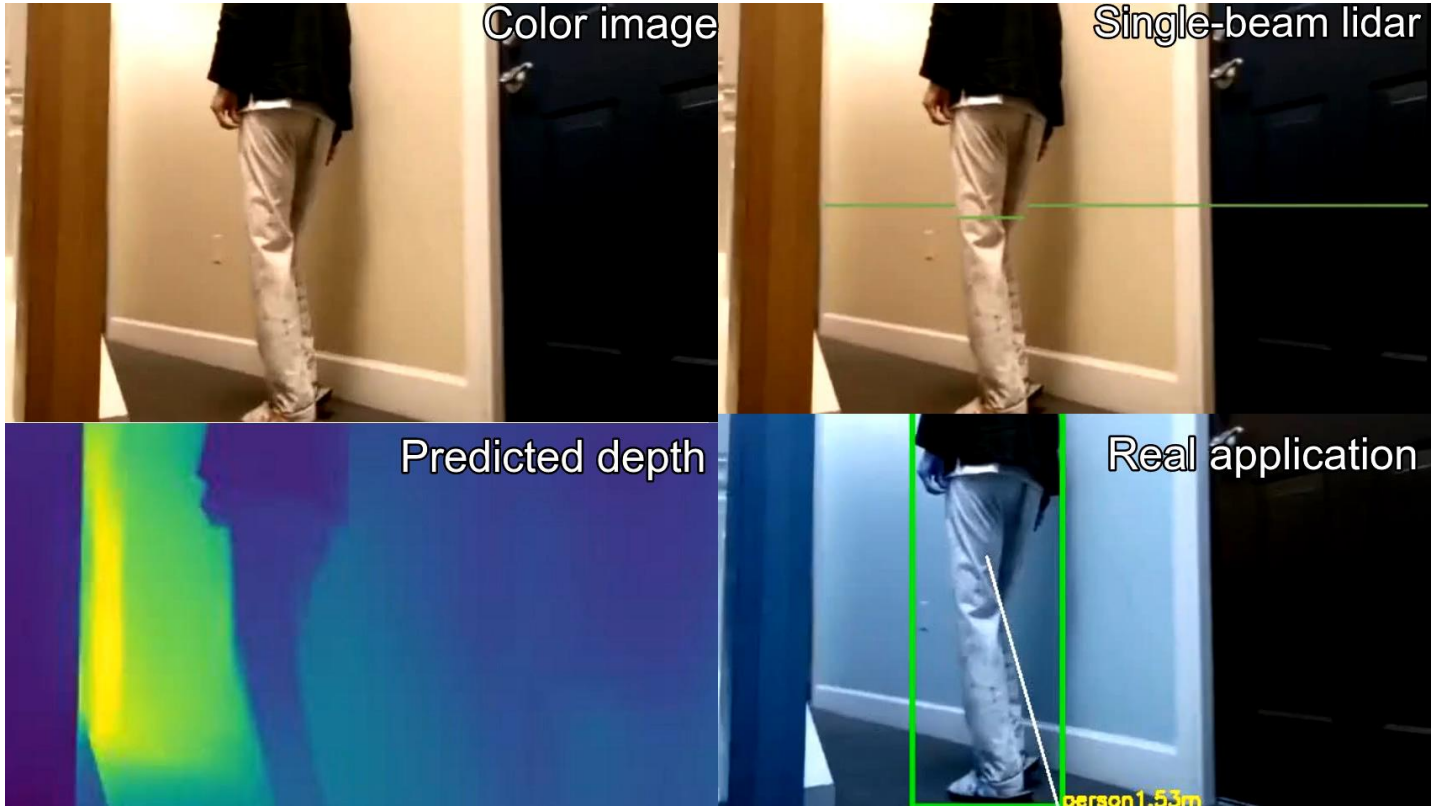


[4] Matteo Poggi, Filippo Aleotti, Fabio Tosi, and Stefano Mattoccia, “Towards real-time unsupervised monocular depth estimation on cpu,”in2018 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS). IEEE, 2018, pp. 5848–5854.

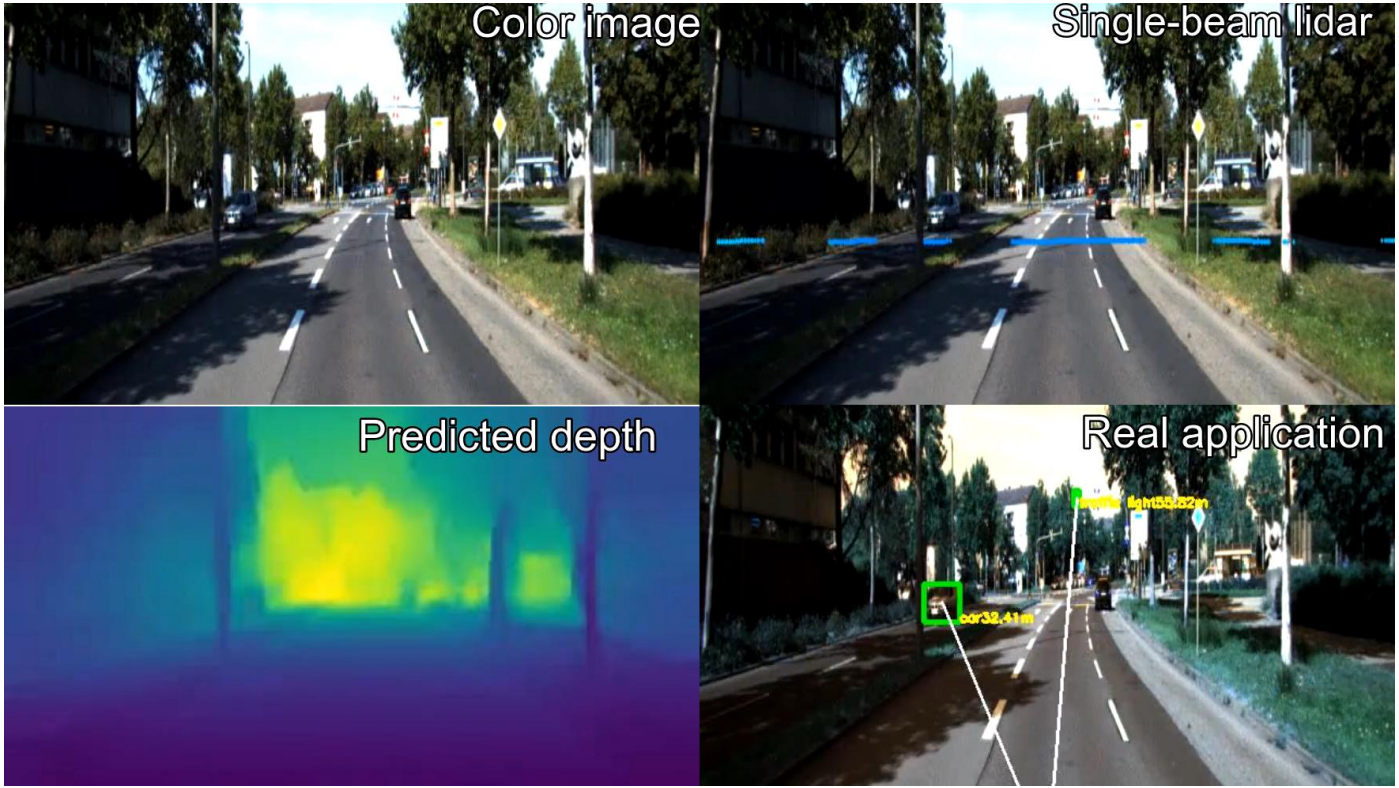
[5] Clement Godard, Oisin Mac Aodha, Michael Firman, and Gabriel Brostow, “Digging into self-supervised monocular depth estimation, ”ICCV, 2019.

[6] Yevhen Kuznietsov, J¨org St¨uckler, and Bastian Leibe, “Semi-supervised deep learning for monocular depth map prediction,” in CVPR, 2017

Indoor demo application



Outdoor demo application



Outline

1. Limitations
2. Contribution
3. Methodology
4. Experimental Results
5. Conclusion

Conclusion

- We propose a deep learning based framework to explore to replicate similar or even higher performance as costly LIDARs with our designed self-supervised network and a low-cost single-beam LIDAR.

Conclusion

- The designed network is able to conduct online learning continuously to refine the output from the disparity estimation network, which enables it to be applied to real-world applications in different scenes.

Conclusion

- To the best of our knowledge, the network is the first to design a deep learning-based framework to explore the application of low-cost single beam LiDAR with single image depth estimation to obtain a high-precision depth sensing from the scenes in full resolution.

Thanks for your attention!