INCORPORATING LUMINANCE, DEPTH AND COLOR INFORMATION BY A FUSION-BASED NETWORK FOR SEMANTIC SEGMENTATION

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Outline

- Introduction
- Method
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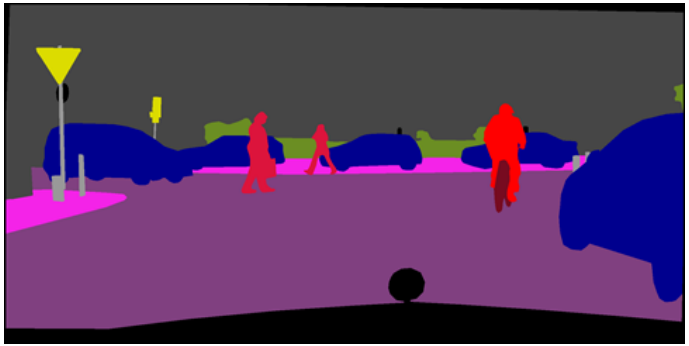
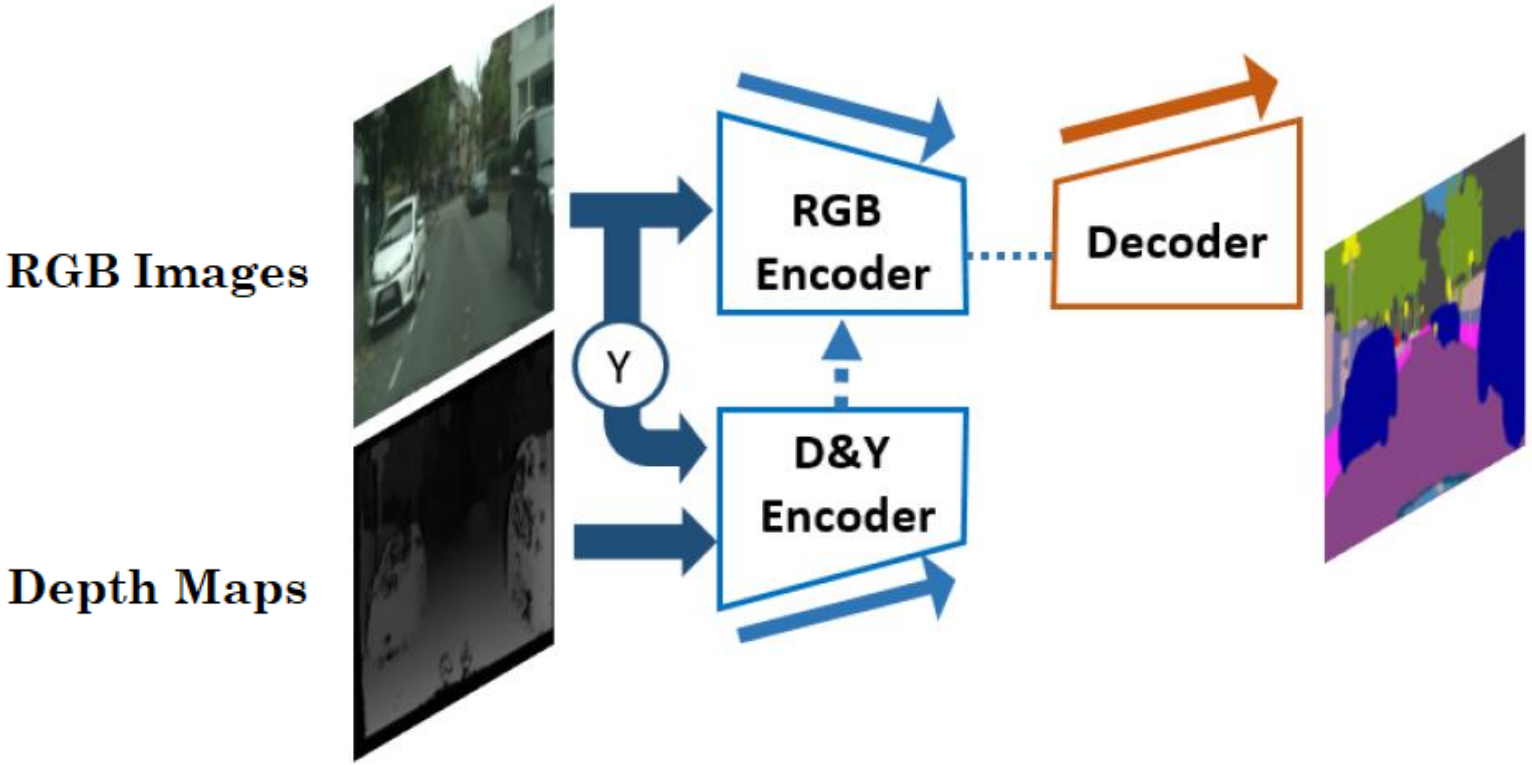
Introduction

Introduction

Road Scene
Semantic Segmentation



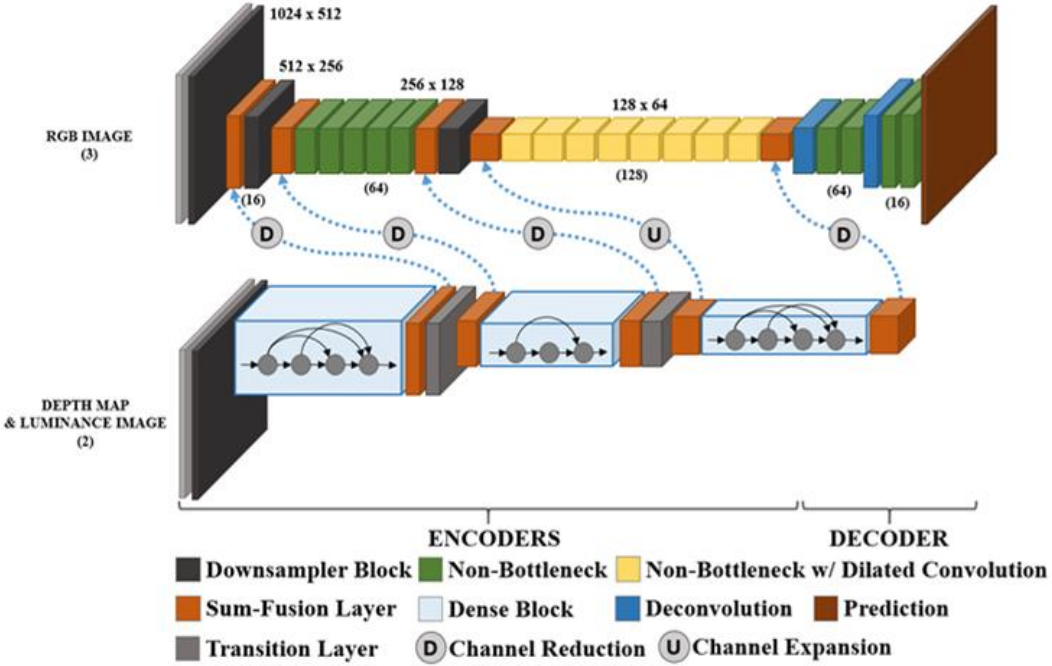
Introduction



Method

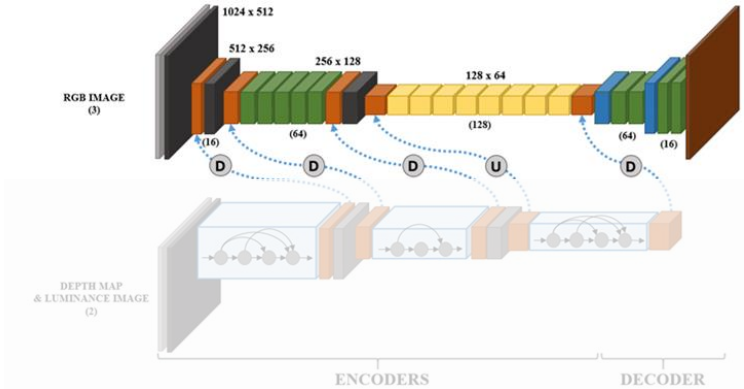
Method

- **RGB Encoder and Decoder**
- **D&Y Encoder**
- **Fusion Mechanism**



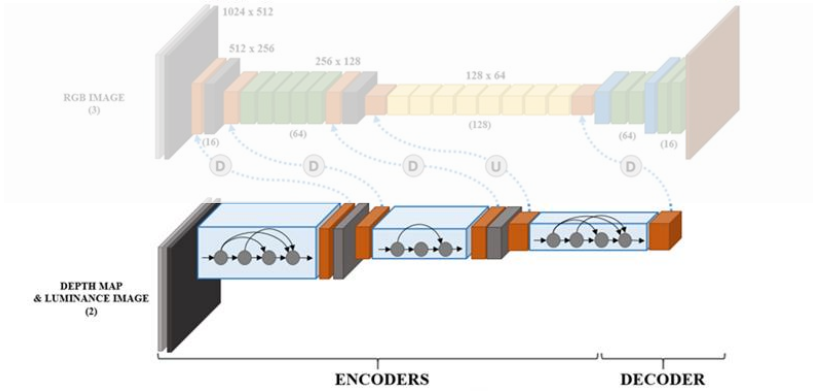
RGB Encoder and Decoder

- Use ERFNet [Romera et al.] as our backbone network.
- Reach good balance between accuracy and complexity.
- Use three downsampler block as encoder.
- Use deconvolution filter as decoder.



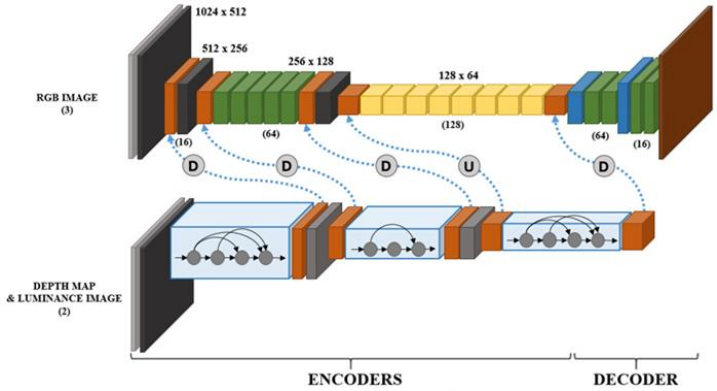
D&Y Encoder

- Adapt from FuseNet [Hazirbas et al.].
- Adopt dense connectivity from DenseNet [Gao et al.].
- Add shallow dense block to extract boundary information.
- Stack luminance images into depth maps to suppress noises.



Fusion Mechanism

- Direct stacking cannot effectively exploit the depth information.
- Conduct fusion operation on different scale.
- Use element-wise summation for each fusion.
- 1×1 convolution layer is used for matching the number of channels.



Experiments

Experiements

- **Implementation Details**
  - Optimizer: Adam
  - Learning rate initialization: 0.0005
  - Learning rate policy: Poly
  - Weight decay: 0.0001
  - Use class weighting : $\omega_{class} = \frac{1}{ln(c+p_{class})}$

Experiements

- **Datasets: Cityscapes**




Ablation Study

- Simply stacking RGB and D channels cannot benefit from the additional depth information.
- Our fusion mechanism is a more effective design for depth information extraction.

Method	RGB Inputs	Depth Maps	Y Info.	Shallow Block	Dense Connects	mIoU (%)	Params
ERFNet-Depth		●				47.48	1.97M
ERFNet-RGB	●					65.59	1.97M
ERFNet-Stack	●	●				65.06	1.97M
LDFNet	●	●	●	●	●	**68.48**	2.31M

Ablation Study

- Adopting dense connectivity can obtain a higher mIoU score with fewer parameters.

Method	RGB Inputs	Depth Maps	Y Info.	Shallow Block	Dense Connects	mIoU (%)	Params
LDF-non-Dense	●	●	●			66.53	2.95M
LDFNet	●	●	●	●	●	**68.48**	2.31M

Ablation Study

- Depth information has a strong correlation to the object edge, contour, and boundary information, so placing Shallow Block at the early stage is beneficial to extract these desired low-level features.

Method	RGB Inputs	Depth Maps	Y Info.	Shallow Block	Dense Connects	mIoU (%)	Params
LDF-w/o-Shallow	●	●	●		●	66.54	2.20M
LDF-58-w/o-Shallow	●	●	●		●	65.93	2.42M
LDFNet	●	●	●	●	●	**68.48**	2.31M

Ablation Study

- Incorporating luminance information achieves a great improvement.

Method	RGB Inputs	Depth Maps	Y Info.	Shallow Block	Dense Connects	mIoU (%)	Params
LDF-w/o-Y	●	●		●	●	65.72	2.31M
LDFNet	●	●	●	●	●	**68.48**	2.31M

Ablation Study

- The increased parameters indeed provide some improvements, but our fusion mechanism of incorporation multi-modal information contributes significantly more.

Method	RGB Inputs	Depth Maps	Y Info.	Shallow Block	Dense Connects	mIoU (%)	Params
ERFNet-RGB	●					65.59	1.97M
LDF-RGB-RGB	●			●	●	67.79	2.31M
LDFNet	●	●	●	●	●	**68.48**	2.31M

Comparison

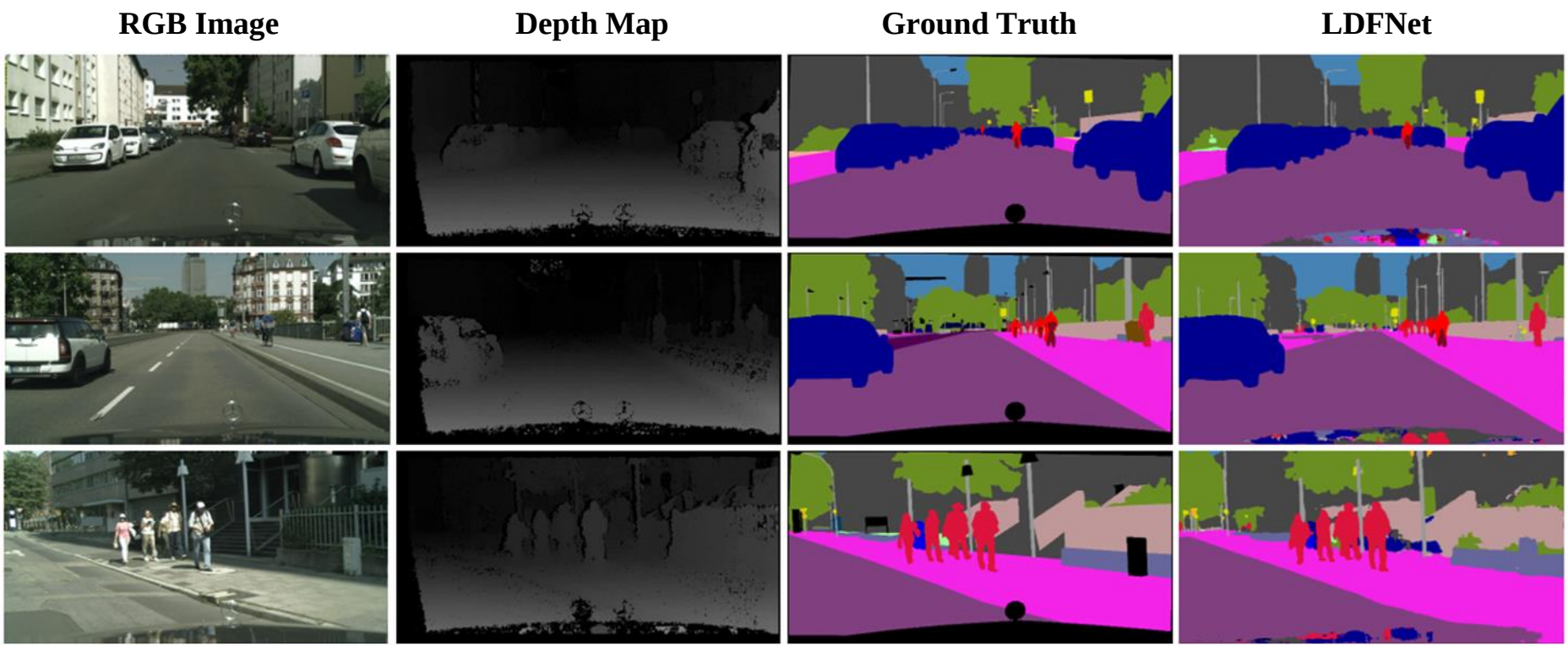
Table 2: Evaluation results on the Cityscapes test set, comparing LDFNet with the other RGB-D methods.

Method	mIoU (%)	Speed (fps)
MultiBoost	59.3	4.0
Pixel-level Encoding [16]	64.3	n/a
Scale invariant CNN+CRF [10]	66.3	n/a
RGB-D FCN	67.4	n/a
LDFNet (ours)	71.3	18.4

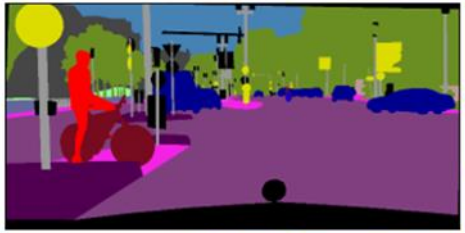
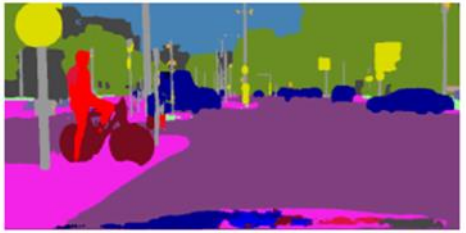
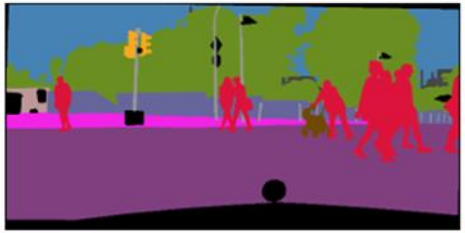
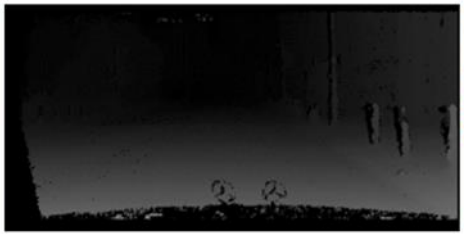
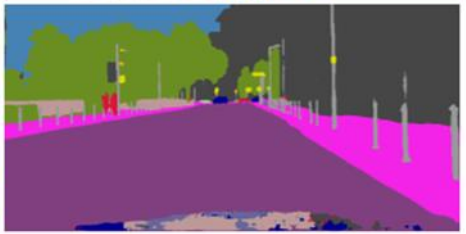
Table 3: Comparison of model efficiency with RGB methods. Sub: the amount of subsampling used by the method at test time.

Method	Parameters	Sub	Speed (fps)
DeepLabv2 [2]	44.0M	no	n/a
PSPNet [20]	65.7M	no	n/a
Dilation10 [19]	140.8M	no	0.25
FCN-8s [12]	134.5M	no	2.0
SegNet [1]	29.5M	4	16.7
LDFNet (ours)	2.31M	2	18.4

Results



Results

RGB Image	Depth Map	Ground Truth	LDFNet
			
			
			

Conclusion

Conclusion

- We propose a novel solution named LDFNet, which incorporates Luminance, Depth and Color information by a fusion-based network.
- It includes a sub-network to process depth maps and employs luminance images to assist the depth information in processes.
- LDFNet outperforms the other state-of-art systems on the Cityscapes dataset, and its inference speed is faster than most of the existing networks.
- The experimental results show the effectiveness of the proposed multi-modal fusion network and its potential for practical applications.

The End

Thank you for your attention