Left-Right Comparative Recurrent Model for stereo Matching

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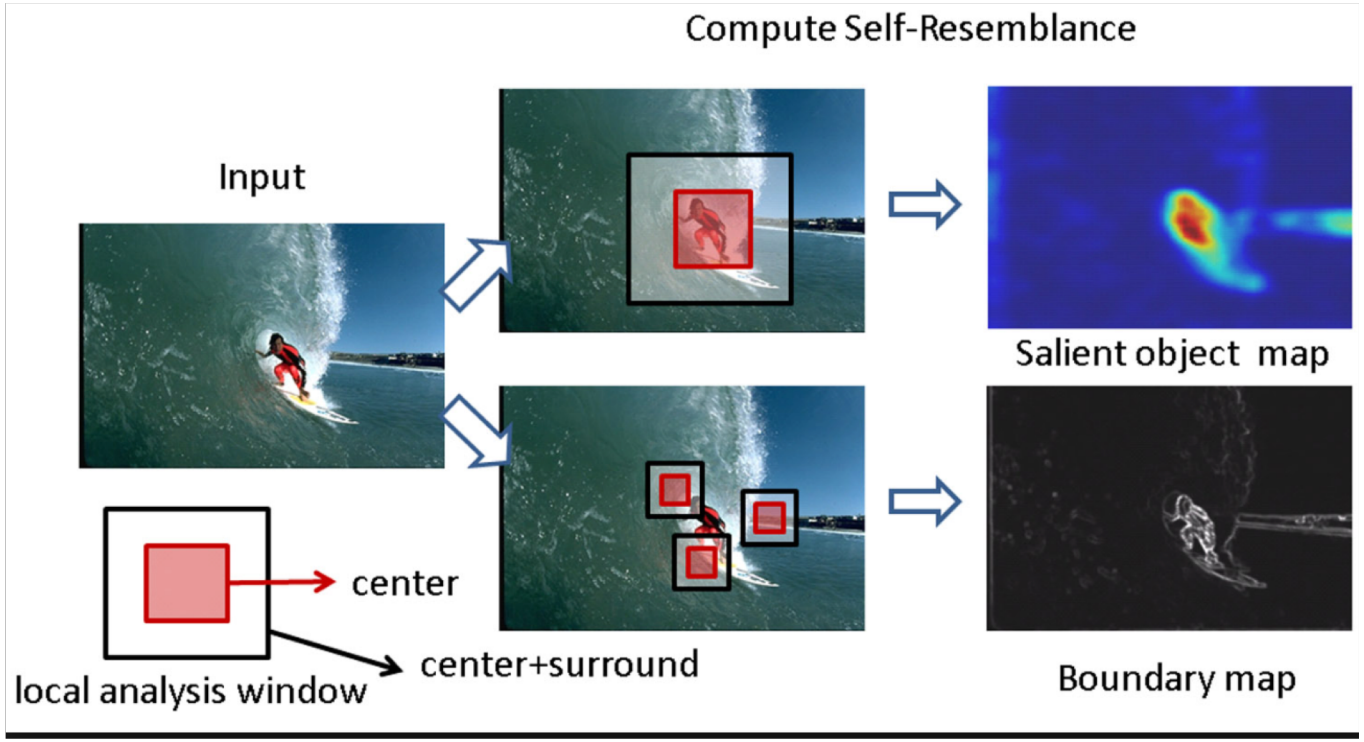
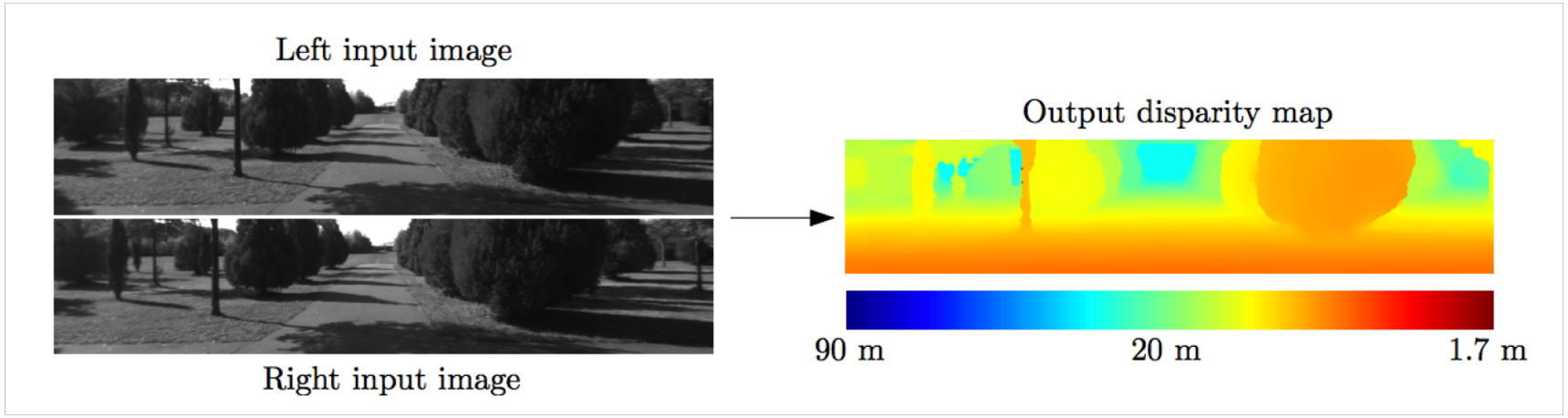
Introduction

- Compute the saliency map in one image



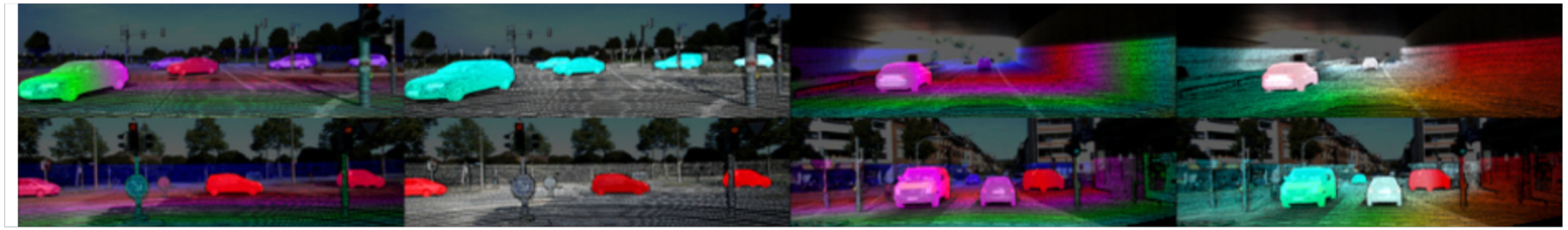
Introduction

- Compute the dense disparity map between a rectifier stereo pair of images
- Core to many computer vision applications, including robotics and antunomous vehicles

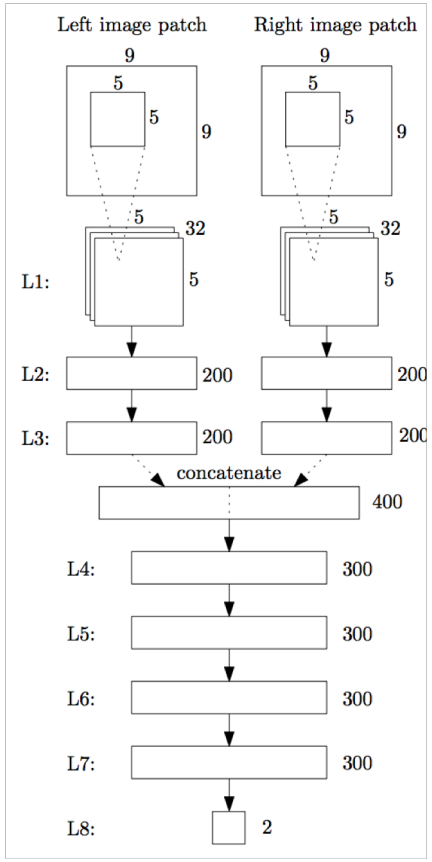


Dataset

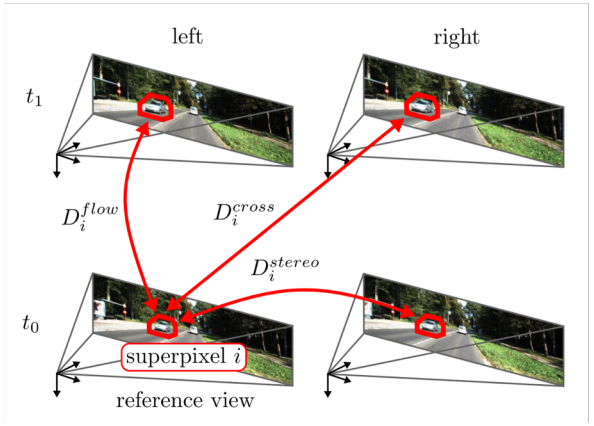
- KITTI 2015 Scene Flow Middlebury



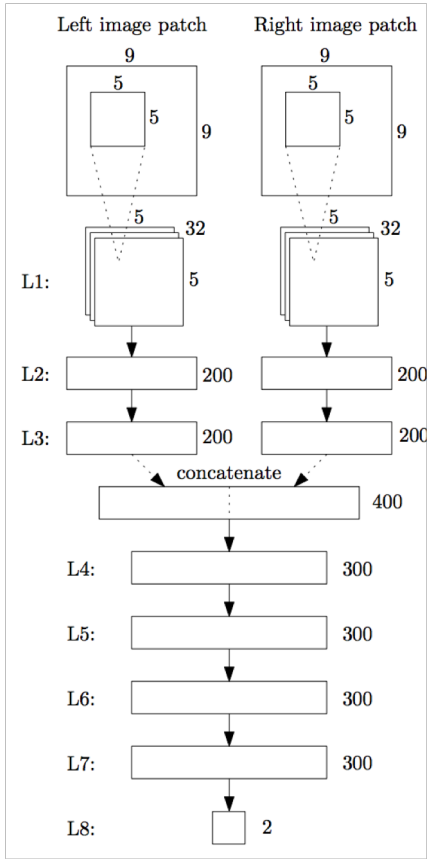
Conventional Methods



$$C_{\text{CNN}}(\mathbf{p}, d) = f_{\text{neg}}(< \mathcal{P}^{L}_{9\times 9}(\mathbf{p}), \mathcal{P}^{R}_{9\times 9}(\mathbf{pd}) >)$$



Conventional Methods



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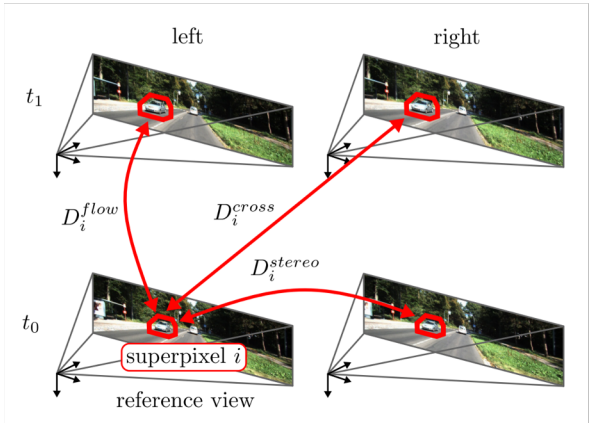
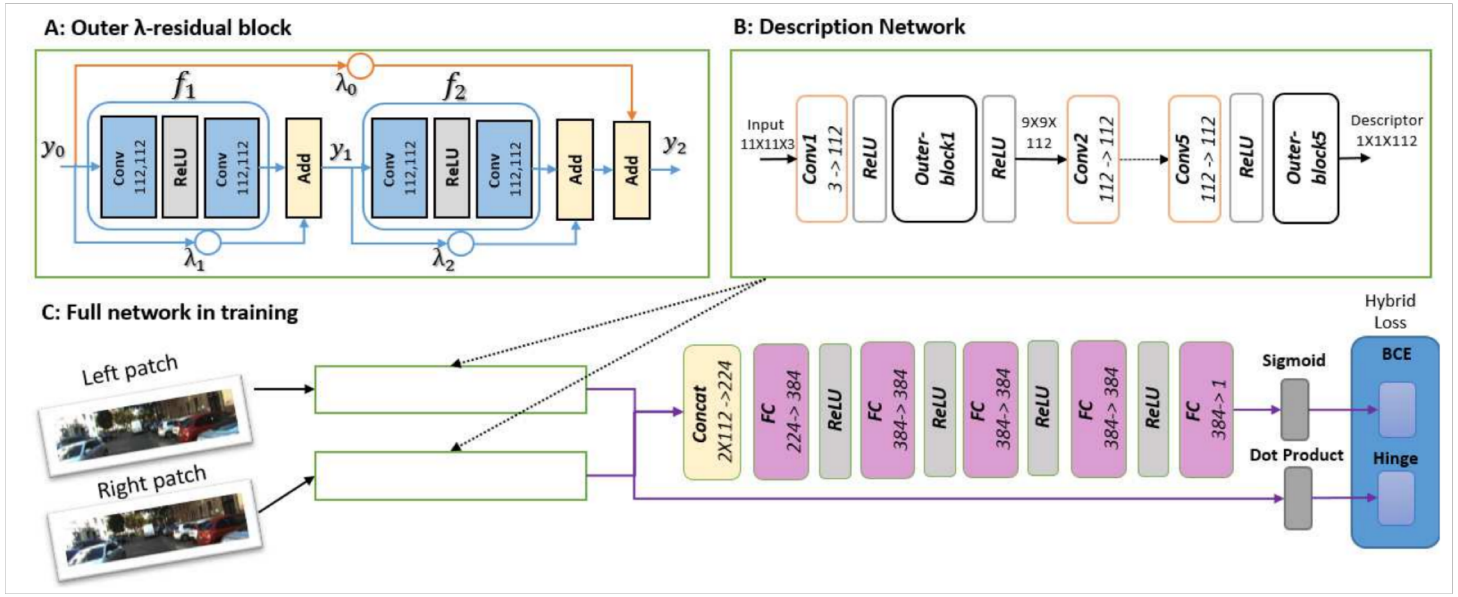
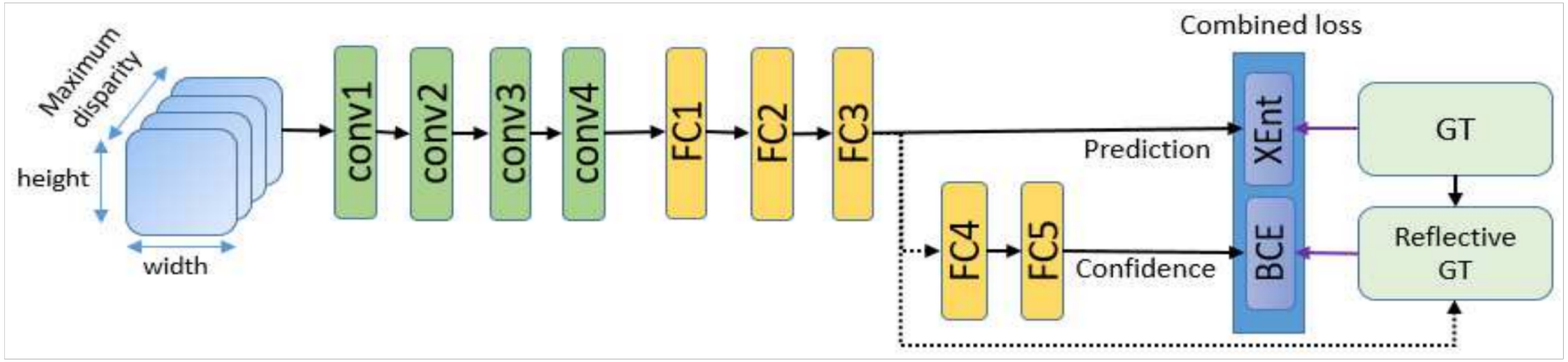




Conventional Methods

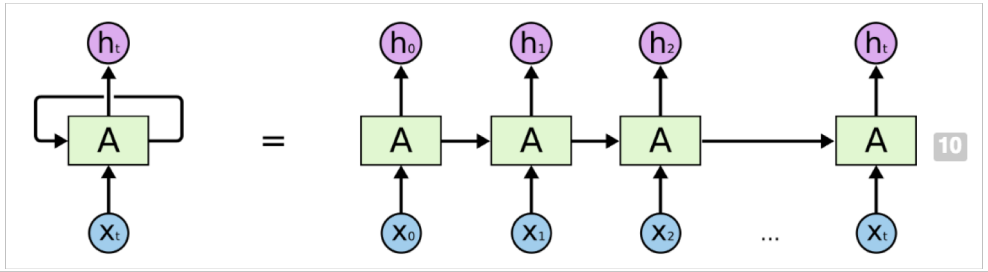


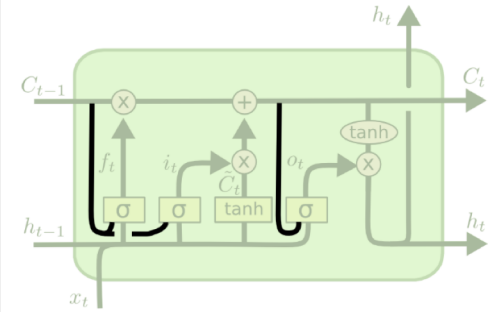
Contribution

- A novel recurrent model for better handling stereo disparity estimation tasks
- A soft attention mechanism is introduced to guide the network to automatically focus more on the unreliable regions
- Perform extensive experiments on KITTI 2015, SceneFlow and Middlebury, and achieve the state-of-the-art results.

Conv-LSTM

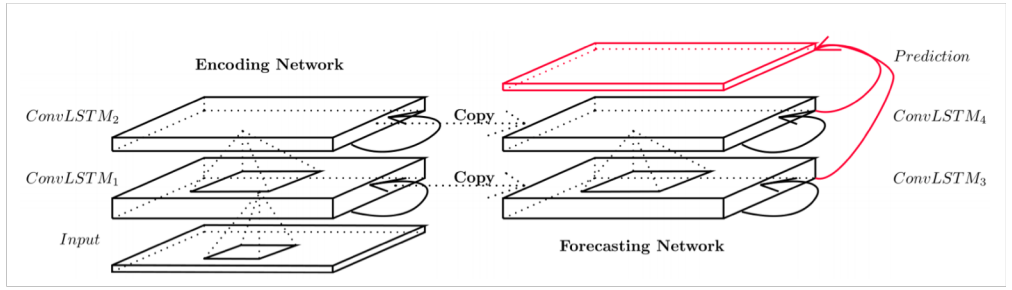
LSTM





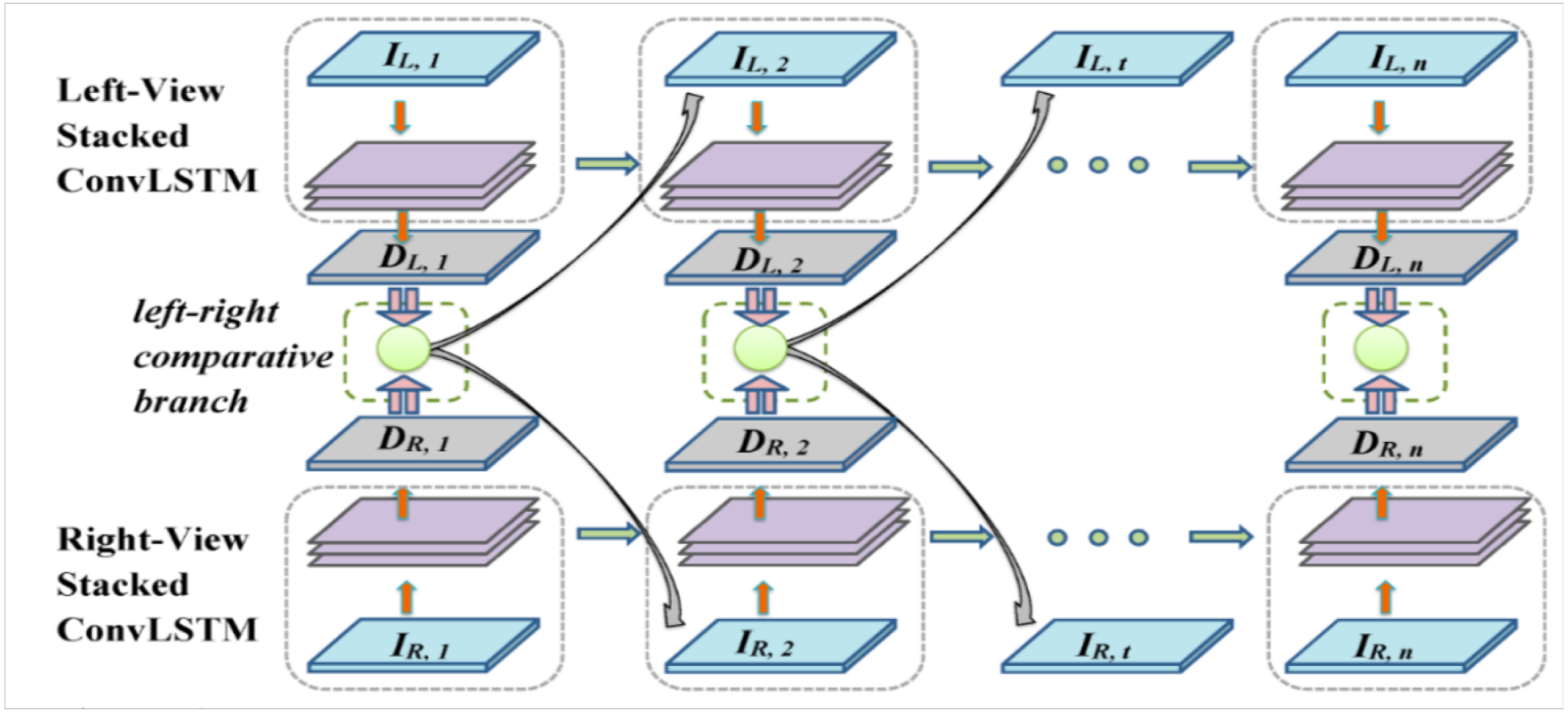
$$f_t = \sigma\left(W_f \cdot [\boldsymbol{C_{t-1}}, h_{t-1}, x_t] \; + \; b_f\right)$$
$$i_t = \sigma\left(W_i \cdot [\boldsymbol{C_{t-1}}, h_{t-1}, x_t] \; + \; b_i\right)$$
$$o_t = \sigma\left(W_o \cdot [\boldsymbol{C_t}, h_{t-1}, x_t] \; + \; b_o\right)$$

Conv-LSTM

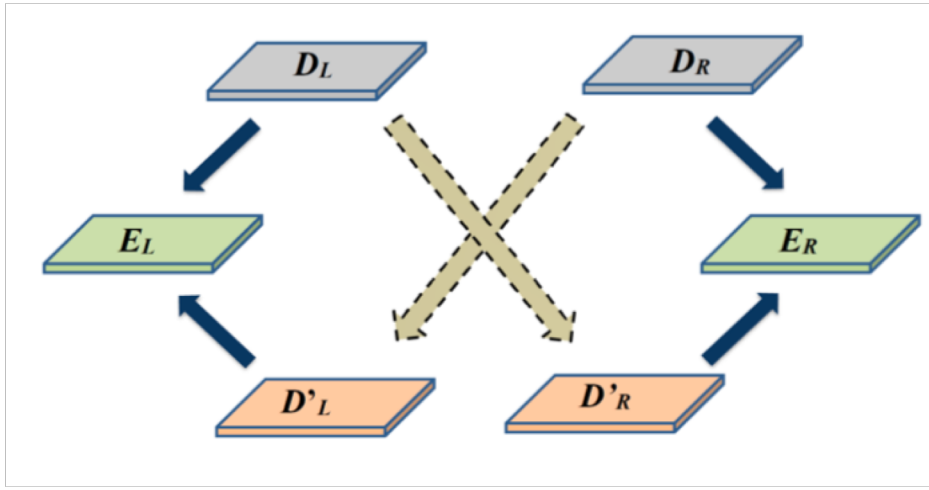


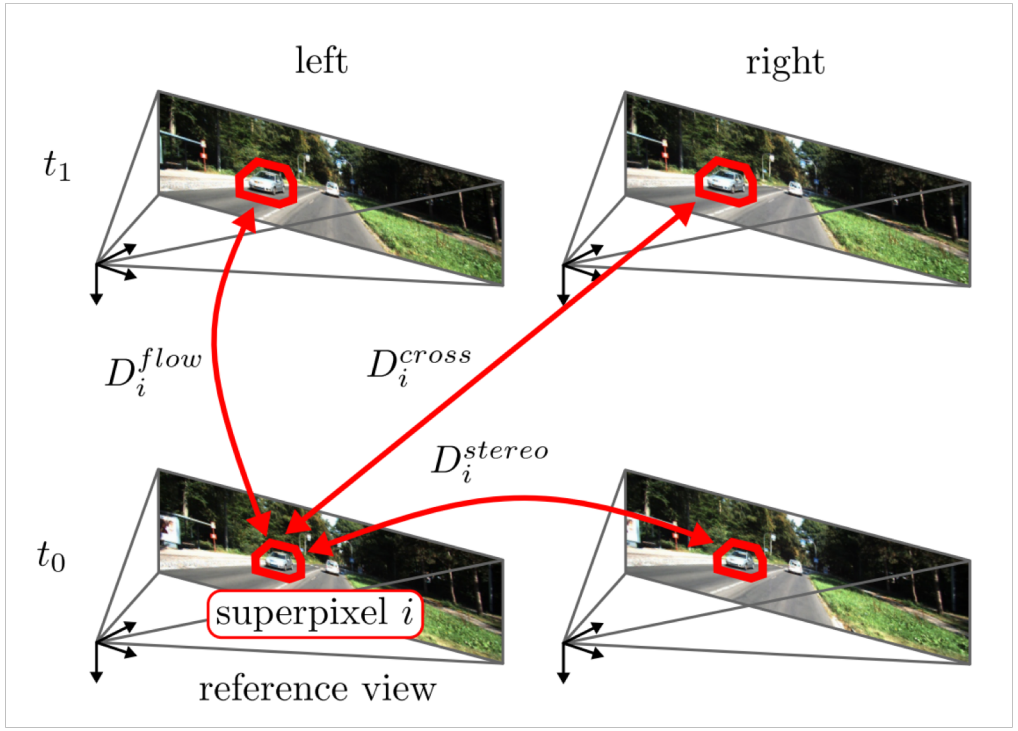
$$i_t = \sigma(W_{xi} * \mathcal{X}_t + W_{hi} * \mathcal{H}_{t-1} + W_{ci} \circ \mathcal{C}_{t-1} + b_i)$$
$$f_t = \sigma(W_{xf} * \mathcal{X}_t + W_{hf} * \mathcal{H}_{t-1} + W_{cf} \circ \mathcal{C}_{t-1} + b_f)$$
$$\mathcal{C}_t = f_t \circ \mathcal{C}_{t-1} + i_t \circ \tanh(W_{xc} * \mathcal{X}_t + W_{hc} * \mathcal{H}_{t-1} + b_c)$$
$$o_t = \sigma(W_{xo} * \mathcal{X}_t + W_{ho} * \mathcal{H}_{t-1} + W_{co} \circ \mathcal{C}_t + b_o)$$
$$\mathcal{H}_t = o_t \circ \tanh(\mathcal{C}_t)$$

Method


Left-View Stacked ConvLSTM
left-right comparative branch
Right-View Stacked ConvLSTM
$I_{L,1}$
$I_{L,2}$
$I_{L,t}$
$I_{L,n}$
$D_{L,1}$
$D_{L,2}$
$D_{L,n}$
$D_{R,1}$
$D_{R,2}$
$D_{R,n}$
$I_{R,1}$
$I_{R,2}$
$I_{R,t}$
$I_{R,n}$

Method


D_L
D_R
E_L
E_R
D'_L
D'_R


left
right
t_1
t_0
D_i^{flow}
D_i^{cross}
D_i^{stereo}
superpixel i
reference view

Result

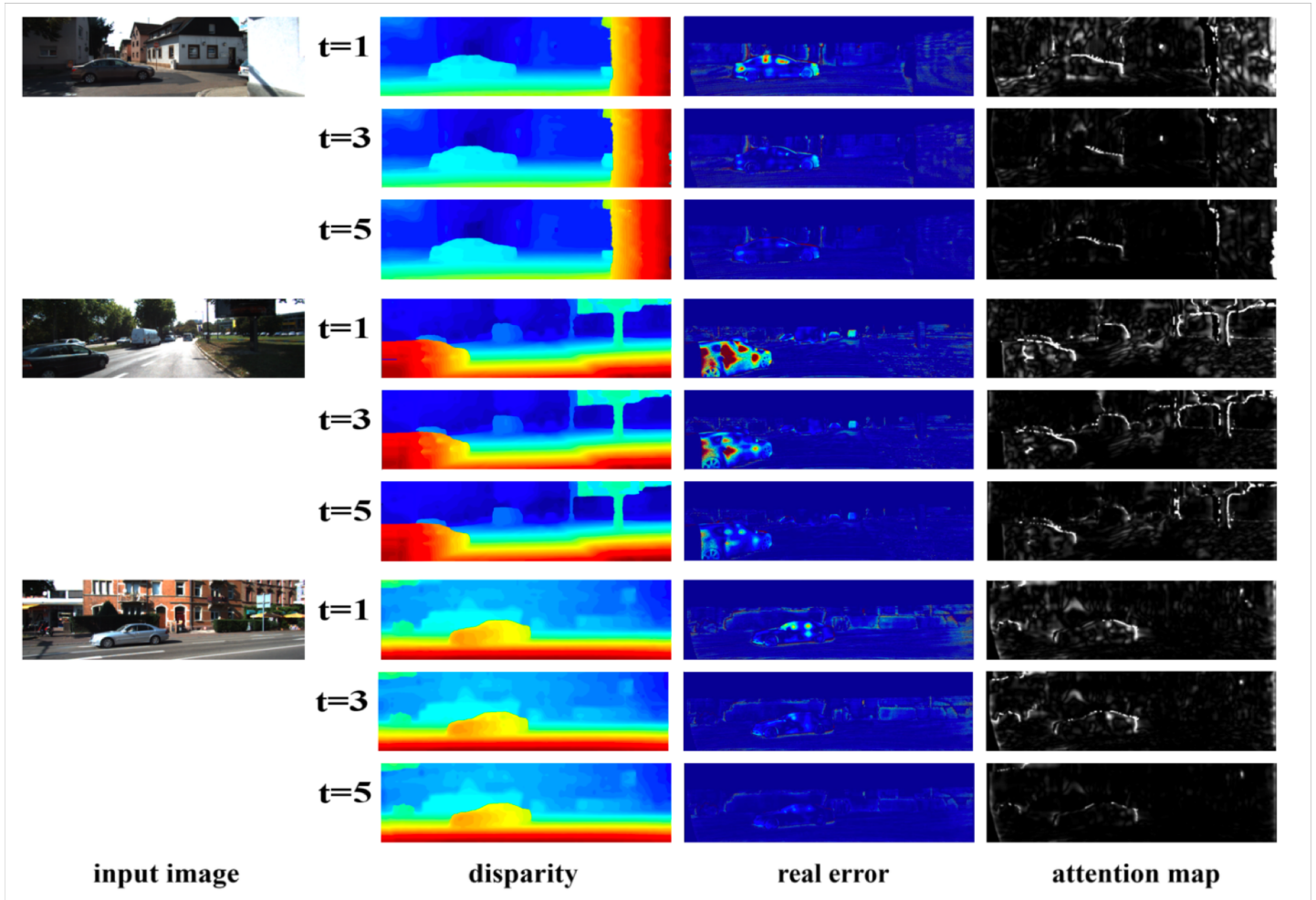
end point error and pixel per- centages with errors larger than 2, 3 and 5 pixels

Model	Recurrent Type	>2 px	>3 px	>5 px	EPE
WTA	–	7.94	4.78	3.11	1.144
Non-recurrent	–	5.70	3.69	2.44	0.939
t=1	w/o comp	6.24	3.92	2.54	0.972
	w/o atten	6.15	3.87	2.53	0.969
	LRCR	6.20	3.90	2.54	0.971
t=2	w/o comp	5.88	3.74	2.46	0.950
	w/o atten	5.79	3.72	2.45	0.945
	LRCR	5.61	3.66	2.42	0.935
t=3	w/o comp	5.64	3.67	2.43	0.936
	w/o atten	5.05	3.44	2.29	0.891
	LRCR	4.85	3.35	2.15	0.877
t=4	w/o comp	5.43	3.61	2.38	0.922
	w/o atten	4.54	3.22	2.08	0.855
	LRCR	4.33	3.12	2.02	0.839
t=5	w/o comp	5.32	3.58	2.36	0.913
	w/o atten	4.14	3.05	1.99	0.825
	LRCR	3.92	2.96	1.93	0.806

error rates of the non-occluded pixels and all the pixels

Type	Method	NOC	ALL	Runtime
Others	MC-CNN-acrt [35]	3.33	3.89	67s
	Content-CNN [15]	4.00	4.54	1s
	Displets v2 [7]	3.09	3.43	265s
	DRR [6]	2.76	3.16	1.4s
End-to-end CNN	GC-NET [13]	2.61	2.87	0.9s
	CRL [21]	2.45	2.67	0.47s
LRCR and the baseline	λ-ResMatch (fast) [29]	3.29	3.78	2.8s
	λ-ResMatch (hybrid) [29]	2.91	3.42	48s
	Ours (fast)	2.79	3.31	4s
	Ours (hybrid)	2.55	3.03	49.2s

Result


t=1
t=3
t=5
t=1
t=3
t=5
t=1
t=3
t=5
input image
disparity
real error
attention map

Reference

- Computing the stereo Matching Cost with a convolutional Neural Network, CVPR 2015
- Object Scene Flow for Autonomous Vehicles, CVPR 2015
- Convolutional LSTM Network:A Machine Learning Approach for Precipitation Newcasting, NIPS 2015
- Improved Stereo Matching with Constant Highway Networks and Reflective Confidence Learning, CVPR 2017