Deep Learning Solutions for Visual World Understanding

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Learning and Vision Group

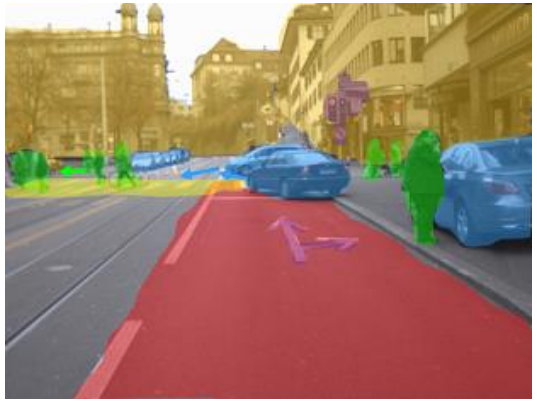
NUS

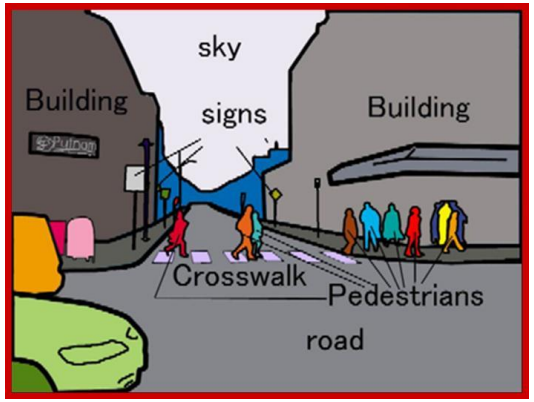
Intelligent Image/video Processing

- **Image/video processing**

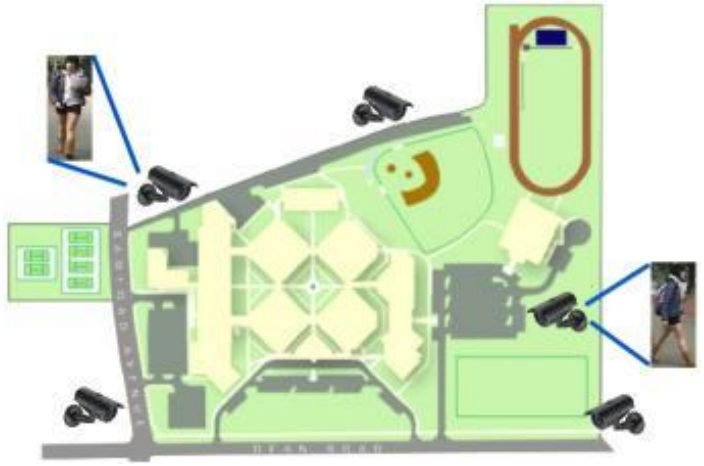
- **Face analysis**

- **Scene Understanding**

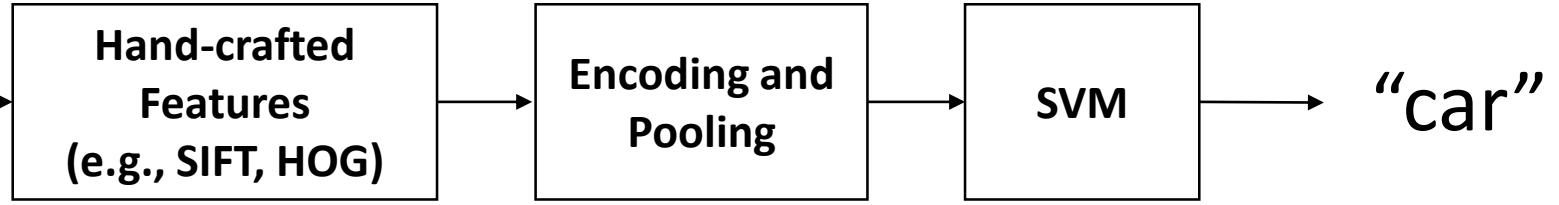




- **Human analysis**

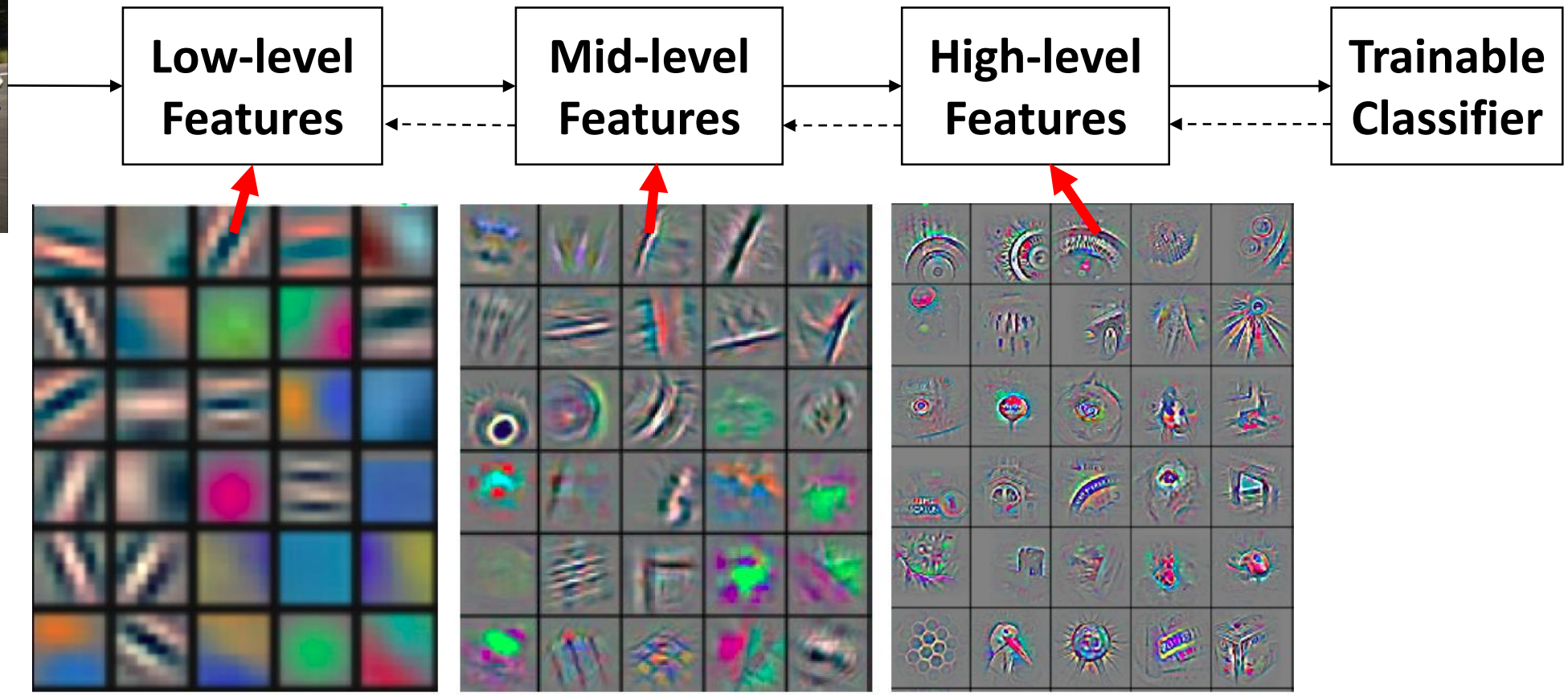


Traditional Approaches



- Heavily relies on expert knowledge
- Same level of abstraction for simple and complicated images.

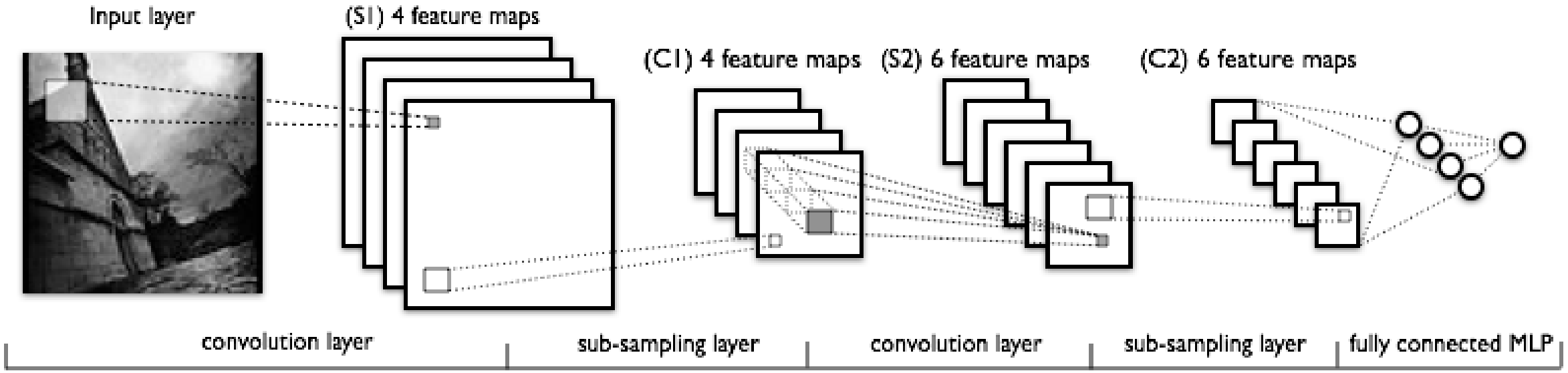
End-to-end Hierarchical Representation Learning Approaches



Feature visualization of convolutional net trained on ImageNet from [Zeiler & Fergus 2013]

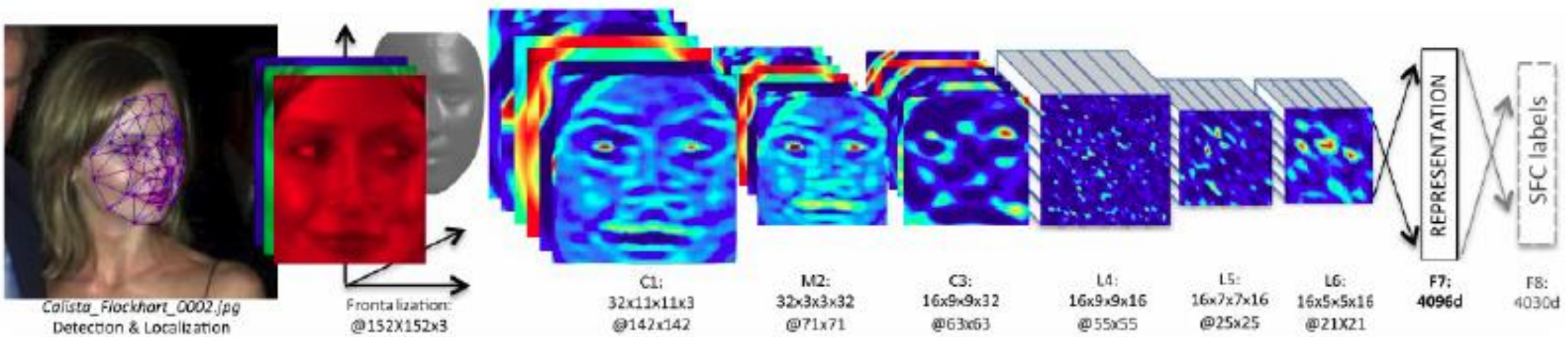
Convolutional Neural Networks

- Each filer is shared over the image plane (convolution)
- Each output sees a large input context (pooling)



[LeCun et al. NIPS 1989]

ConvNets for Visual Understanding
- Face recognition



- Deep face
- Alignment + ConvNet feature learning + metric learning
- Deployed at Facebook for auto tagging

[Taigman et al. CVPR 2014]

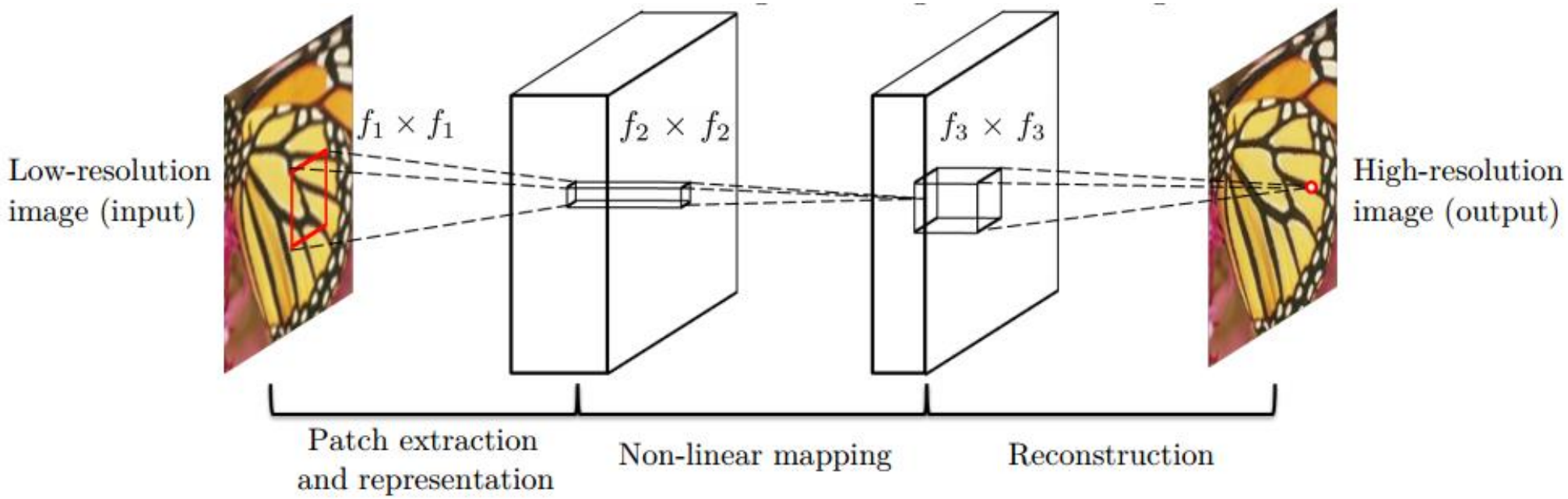
ConvNets for Visual Understanding
- Face detection & pose estimation

ConvNets for Visual Understanding
- Scene parsing

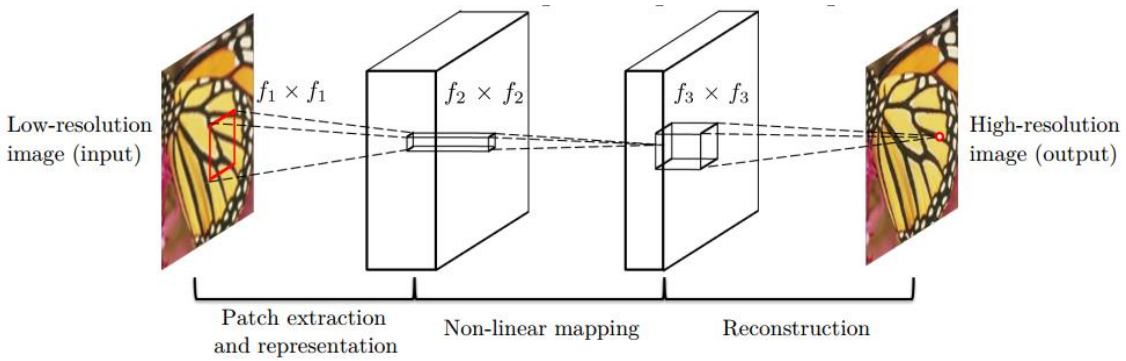
- No post-processing
- Frame by frame
- ConvNet runs at 50 ms/frame on Virtex-6 FPGA hardware

[Farabet et al. ICML 2012, PAMI 2013]

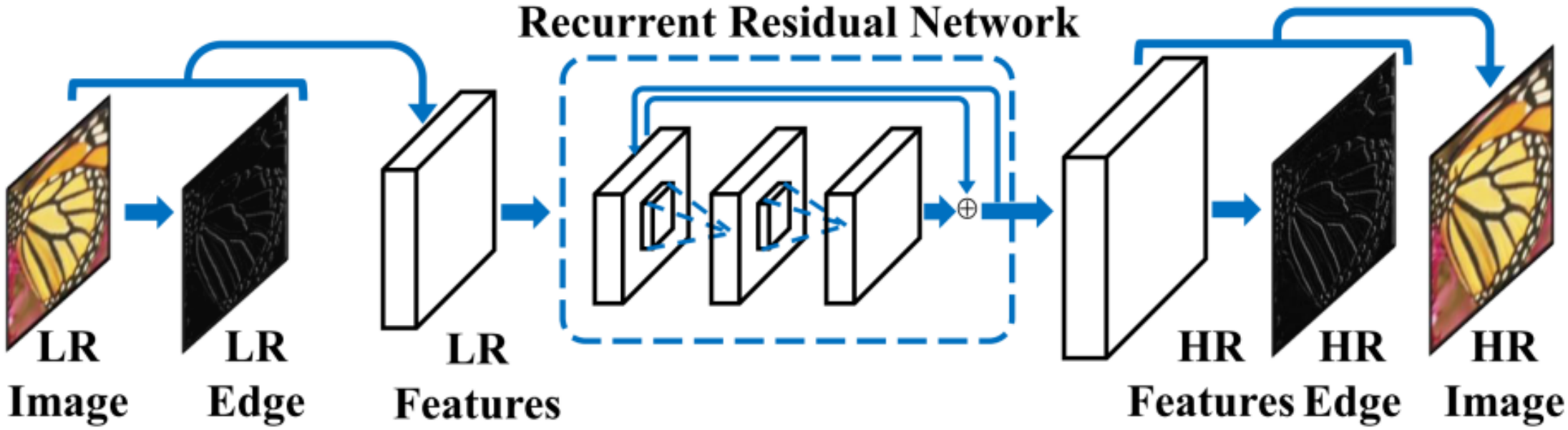
Application I – Deep Image Super-resolution



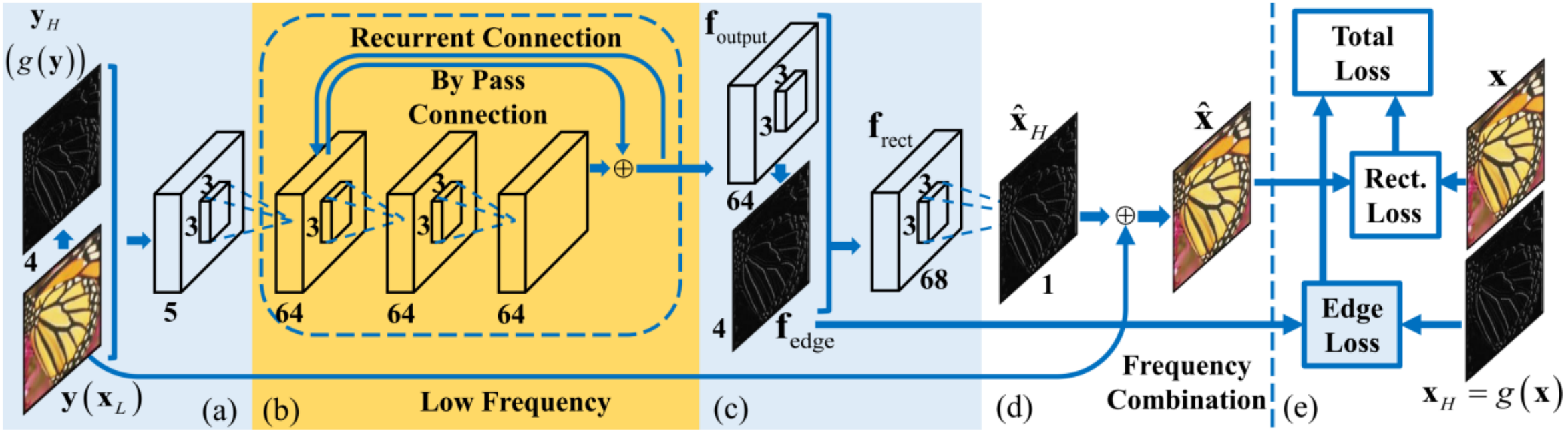
Application I – Deep Image Super-resolution



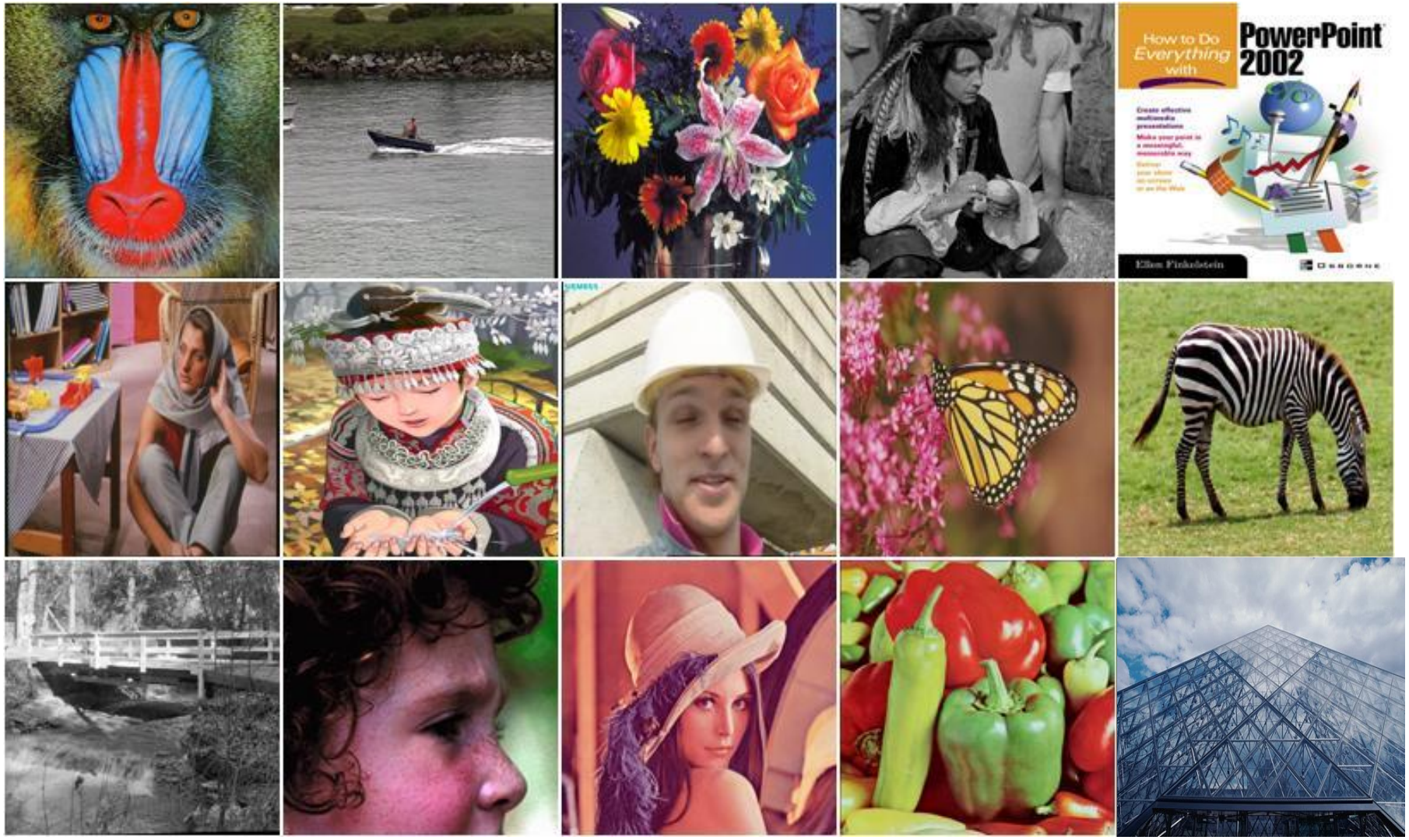
- Exploit the edge-prior
- Recurrently super-resolve images



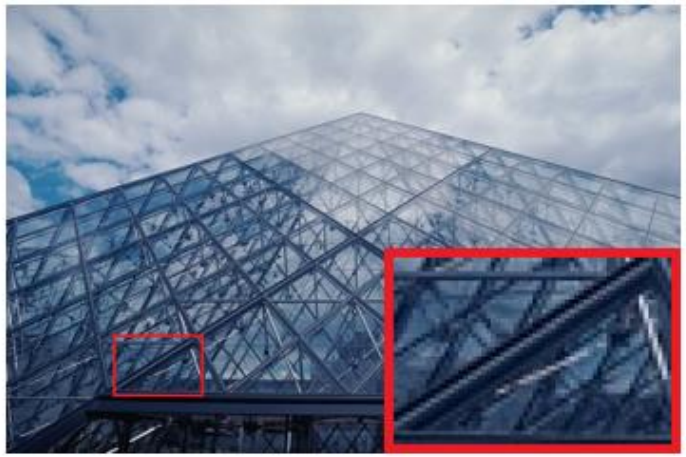
Recurrent Residue ConvNet for Image SR



Deep Image SR Results



Deep Image SR Results



(a) High-res

(b) A+

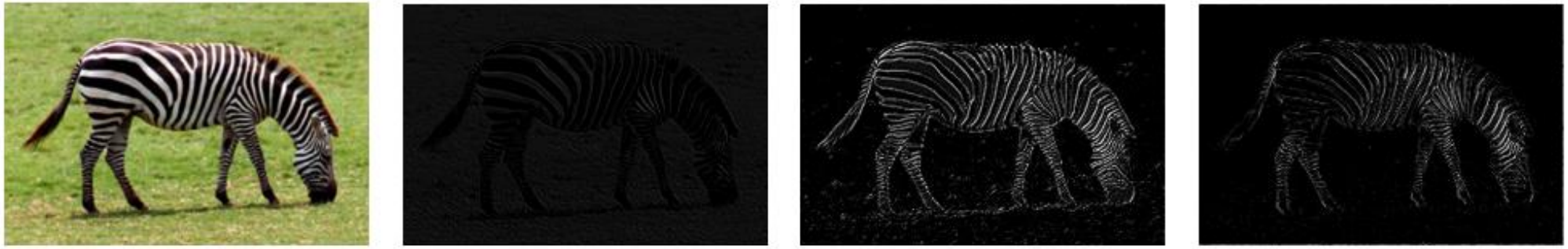
(c) SRCNN

(d) TSE-SR

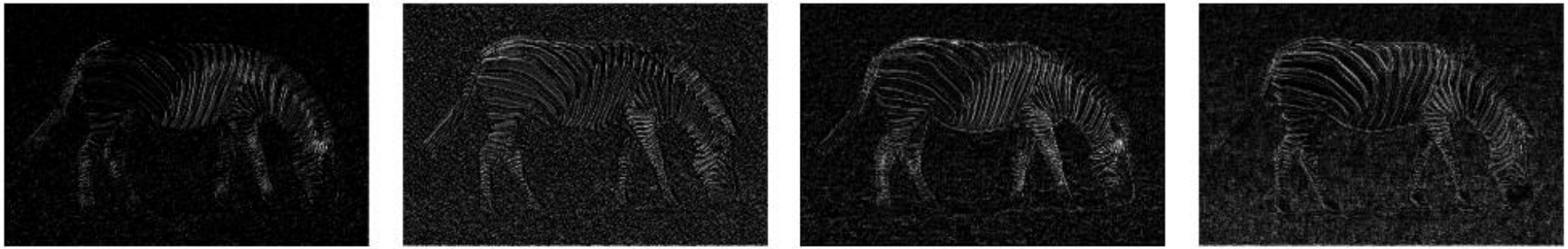
(e) CSCN

(f) DEGREE

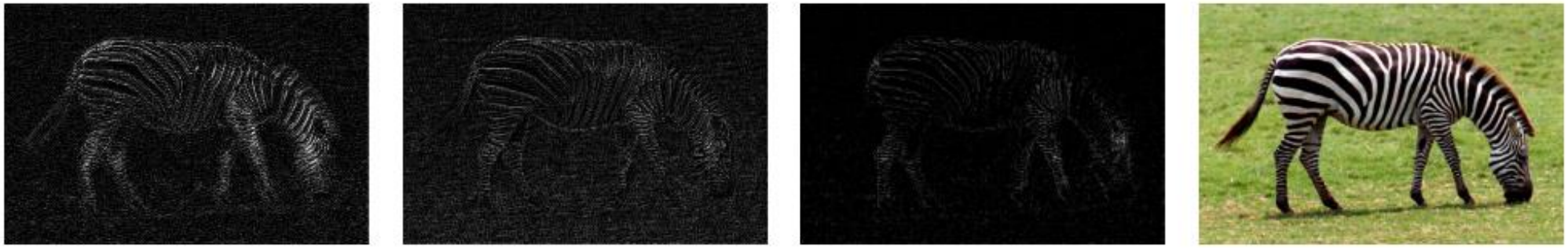
Learned Features at Different Layers



(a) LR (b) 1L (c) 1R (d) 2R



(e) 3R (f) 4R (g) 5R (h) 6R



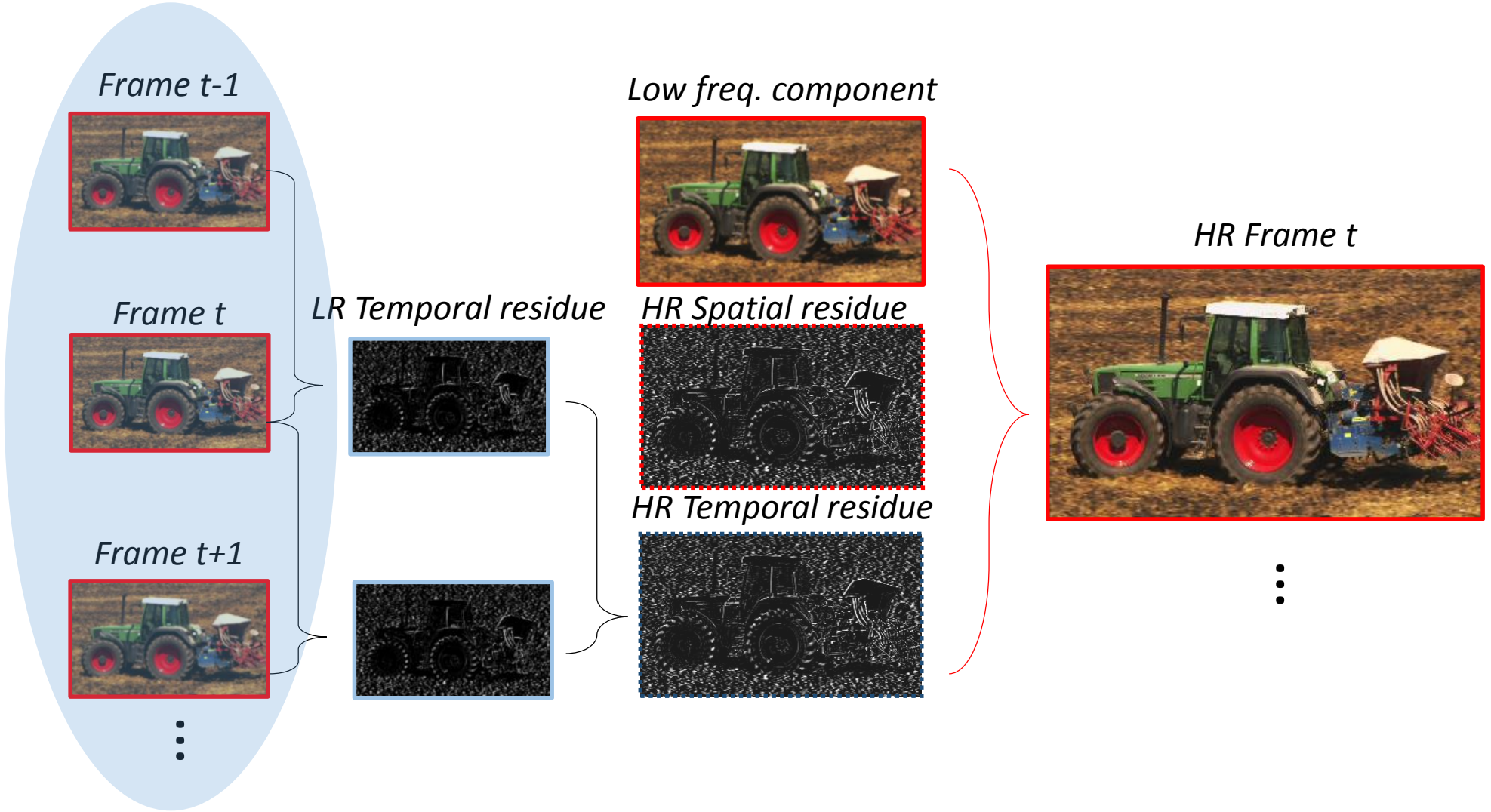
(i) 7R (j) 8R (k) 9R (l) Result

Deep Image SR Results

Dataset		Set5			Set14			BSD100		
Method	Metric	×2	×3	×4	×2	×3	×4	×2	×3	×4
Bicubic	PSNR	33.66	30.39	28.42	30.13	27.47	25.95	29.55	27.20	25.96
	SSIM	0.9096	0.8682	0.8105	0.8665	0.7722	0.7011	0.8425	0.7382	0.6672
ScSR	PSNR	35.78	31.34	29.07	31.64	28.19	26.40	30.77	27.72	26.61
	SSIM	0.9485	0.8869	0.8263	0.8990	0.7977	0.7218	0.8744	0.7647	0.6983
A+	PSNR	36.56	32.60	30.30	32.14	29.07	27.28	30.78	28.18	26.77
	SSIM	0.9544	0.9088	0.8604	0.9025	0.8171	0.7484	0.8773	0.7808	0.7085
TSE-SR	PSNR	36.47	32.62	30.24	32.21	29.14	27.38	31.18	28.30	26.85
	SSIM	0.9535	0.9092	0.8609	0.9033	0.8194	0.7514	0.8855	0.7843	0.7108
JSB-NE	PSNR	36.59	32.32	30.08	32.34	28.98	27.22	31.22	28.14	26.71
	SSIM	0.9538	0.9042	0.8508	0.9058	0.8105	0.7393	0.8869	0.7742	0.6978
CNN	PSNR	36.34	32.39	30.09	32.18	29.00	27.20	31.11	28.20	26.70
	SSIM	0.9521	0.9033	0.8530	0.9039	0.8145	0.7413	0.8835	0.7794	0.7018
CNN-L	PSNR	36.66	32.75	30.49	32.45	29.30	27.50	31.36	28.41	26.90
	SSIM	0.9542	0.9090	0.8628	0.9067	0.8215	0.7513	0.8879	0.7863	0.7103
CSCN	PSNR	36.88	33.10	30.86	32.50	29.42	27.64	31.40	28.50	27.03
	SSIM	0.9547	0.9144	0.8732	0.9069	0.8238	0.7573	0.8884	0.7885	0.7161
CSCN-MV	PSNR	37.14	33.26	31.04	32.71	29.55	27.76	31.54	28.58	27.11
	SSIM	0.9567	0.9167	0.8775	0.9095	0.8271	0.762	0.8908	0.791	0.7191
DEGREE-1	PSNR	37.29	33.29	30.88	32.87	29.53	27.69	31.66	28.59	27.06
	SSIM	0.9574	0.9164	0.8726	0.9103	0.8265	0.7574	**0.8962**	0.7916	0.7177
DEGREE-2	PSNR	37.40	33.39	31.03	32.96	29.61	27.73	31.73	28.63	27.07
	SSIM	0.9580	0.9182	0.8761	0.9115	0.8275	0.7597	0.8937	0.7921	0.7177
DEGREE-MV	PSNR	**37.61**	**33.70**	**31.30**	**33.11**	**29.77**	**27.92**	**31.84**	**28.76**	**27.18**
	SSIM	**0.9589**	**0.9212**	**0.8807**	**0.9129**	**0.8309**	**0.7637**	0.8951	**0.7956**	**0.7207**
Gain	PSNR	0.47	0.45	0.26	0.40	0.22	0.16	0.30	0.18	0.07
	SSIM	0.0022	0.0045	0.0032	0.0034	0.0038	0.0017	0.0043	0.0046	0.0016

CSCN: Wang et al. CVPR 2015
CNN, CNN-L: Dong et al. TPAMI 2015
A+: Timofte et al. ACCV 2014
JSB-NE: Song et al. ICASSP 2016

Deep Video SR



Spatial-Temporal Recurrent Residual Networks for Video Super-Resolution

Supplementary Material

Deep Video SR Results (4x)

(i) VE

(j) 3DSKR

(k) BRCN

(l) STR-ResNet

(m) Details of VE

(n) Details of 3DSKR

(o) Details of BRCN

(p) Details of STR-ResNet

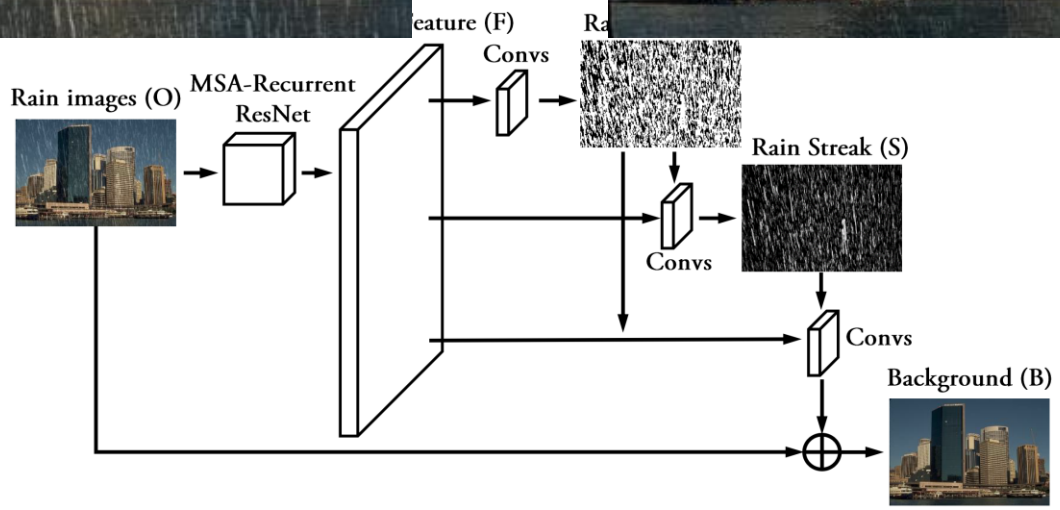
Deep Video SR Results (4x)

	Bicubic	A+	SRCNN	VE	3DKR	DRAFT (5)	DRAFT (31)	BRCN	STR-ResNet
Tractor	31.10	32.07	32.13	31.27	32.27	31.73	30.34	33.23	**33.85**
Sunflower	37.85	38.87	38.69	37.55	37.57	35.62	36.43	39.28	**40.02**
Blue sky	28.77	30.02	30.16	29.19	29.74	30.34	30.92	31.40	**32.23**
Station2	33.35	34.26	34.38	33.36	34.80	32.99	33.22	35.20	**35.63**
Pedestrian	33.51	34.43	34.55	33.60	33.91	33.40	31.78	34.95	**35.22**
Rush_hour	38.17	39.15	38.90	37.96	37.49	36.93	36.22	39.86	**40.30**
Average	33.79	34.80	34.80	33.82	34.30	33.50	33.15	35.65	**36.21**

Degradation: blurred with 9 × 9 Gaussian filters with blur level 1.6
Sequences are from: https://media.xiph.org/video/derf/

[VE] A commercial software: http://www.infognition.com/videoenhancer/.
[3DSKR] H. Takeda, P. Milanfar, M. Protter, and M. Elad. Super-resolution without explicit subpixel motion estimation, TIP. 18(9):1958–1975, 2009.
[DRAFT] R. Liao, X. Tao, R. Li, Z. Ma, and J. Jia. Video super-resolution via deep draft-ensemble learning. June 2015.
[BRCN] Y. Huang, W. Wang, and L. Wang. Bidirectional recurrent convolutional networks for multi-frame super-resolution. In NIPS. 2016.

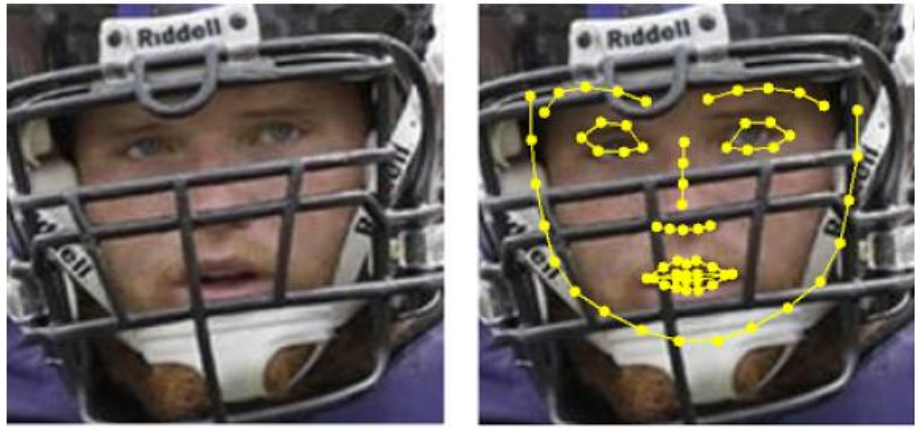
Other Image Processing Applications



Application II - Extreme Face Analysis

Extreme Face Analysis

- Two most challenging issues in face analysis
  - Heavy occlusions
  - Aging issues

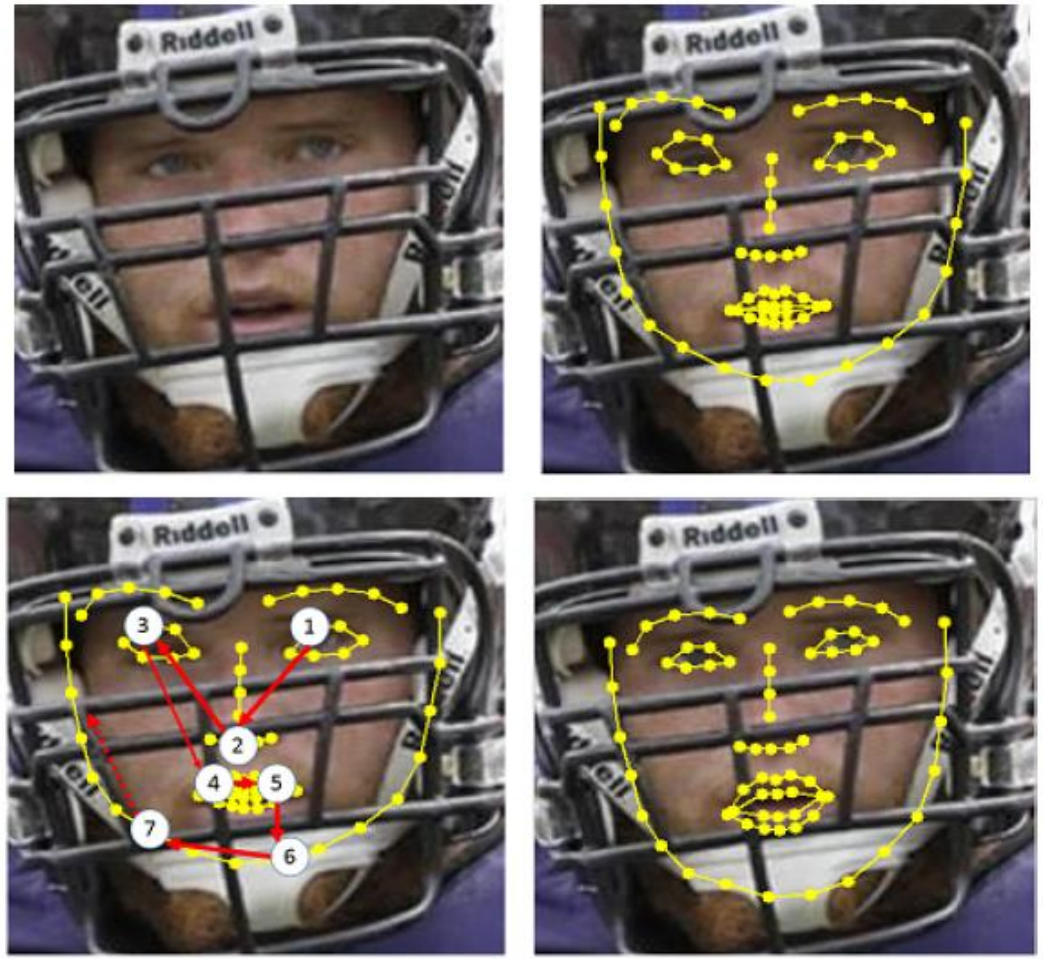


Landmark detection

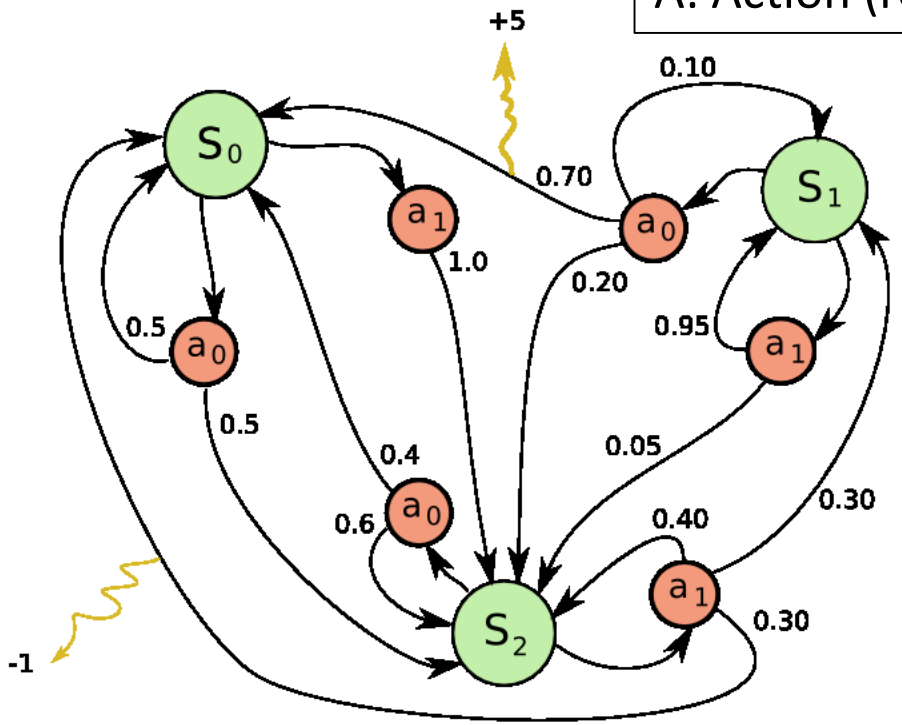
Same person?

Yes: Mickey Rourke

Occlusion-Robust Face Alignment

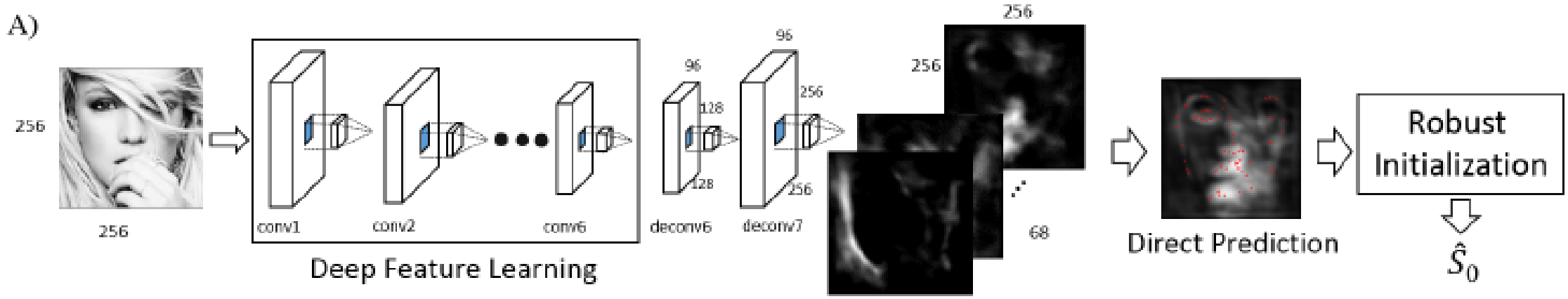


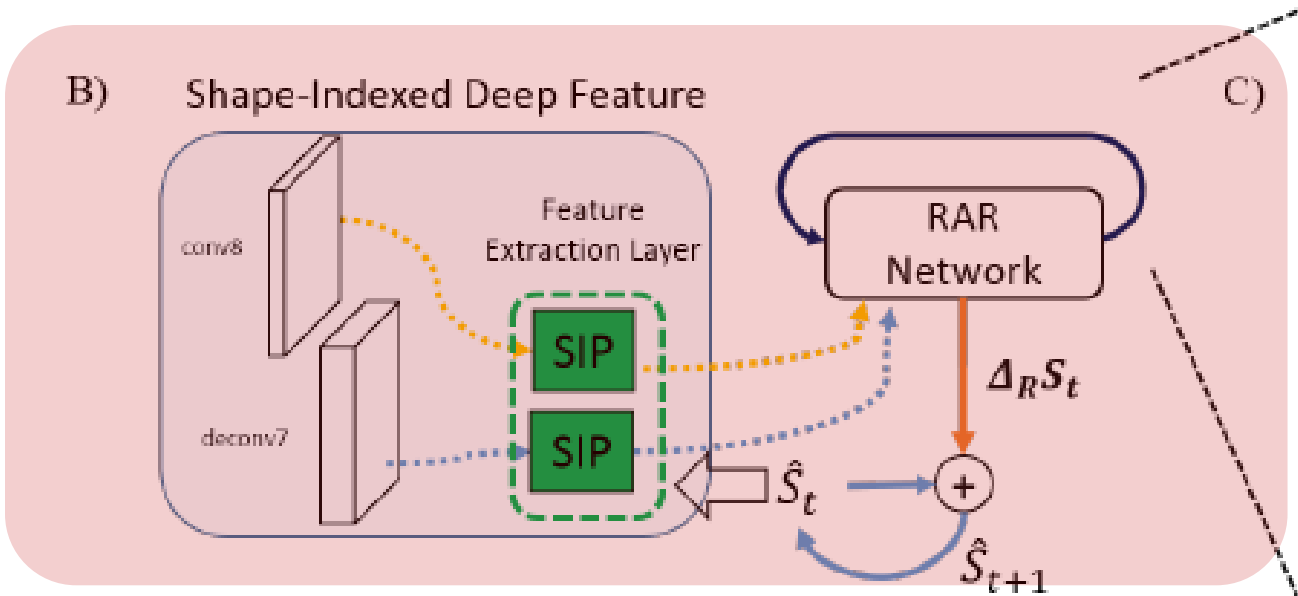
S: State (landmark)
A: Action (refinement)

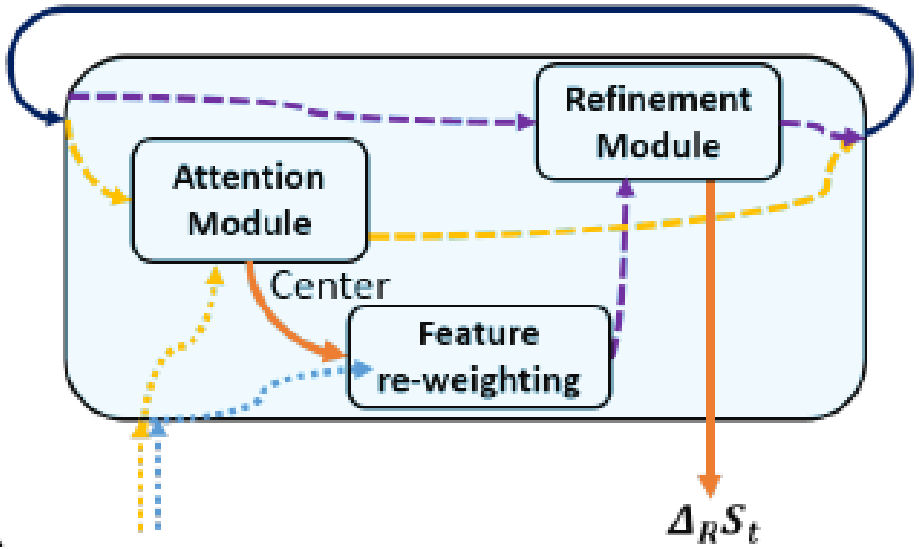


- Robust to heavy occlusions
- Efficient – encouraging good detection in early steps

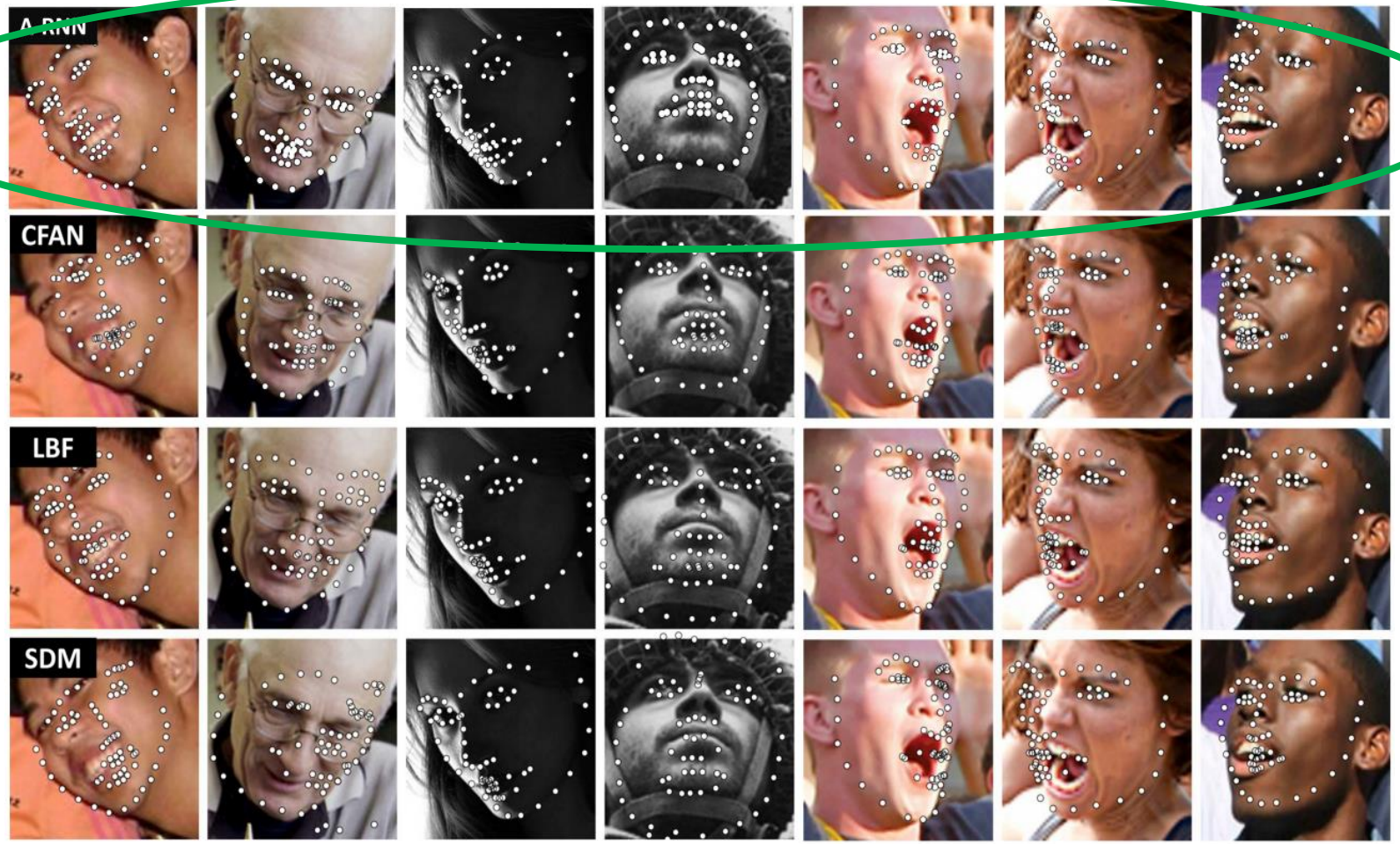
Recurrent Attentive Networks







Robust Face Alignment Results



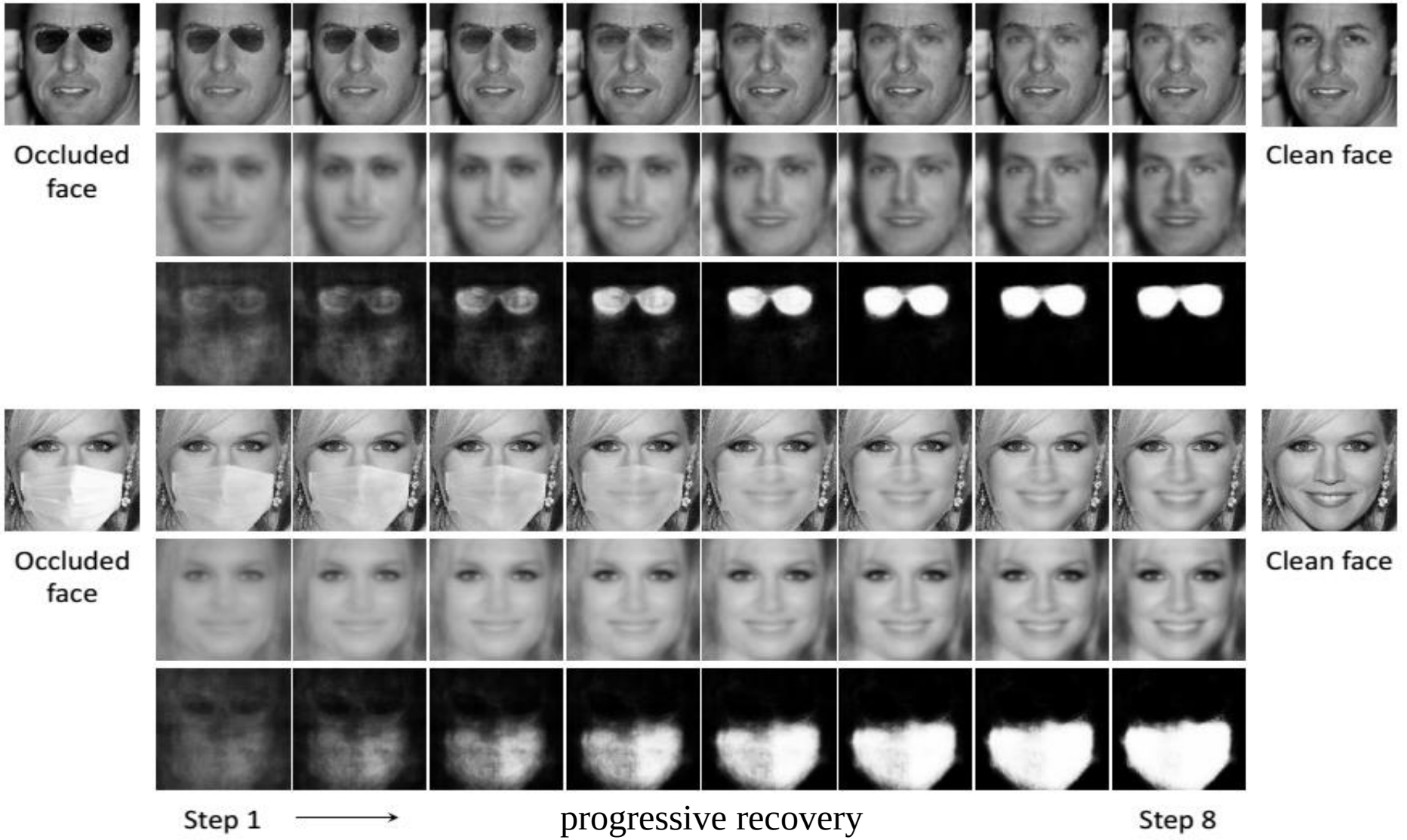
CFAN: Coarse-to-fine auto-encoder networks (cfan) for real-time face alignment. ECCV 2014
LBF: Face alignment at 3000 fps via regressing local binary features. ECCV 2014
SDM: Supervised descent method and its applications to face alignment. CVPR 2013

Robust Face Alignment Results

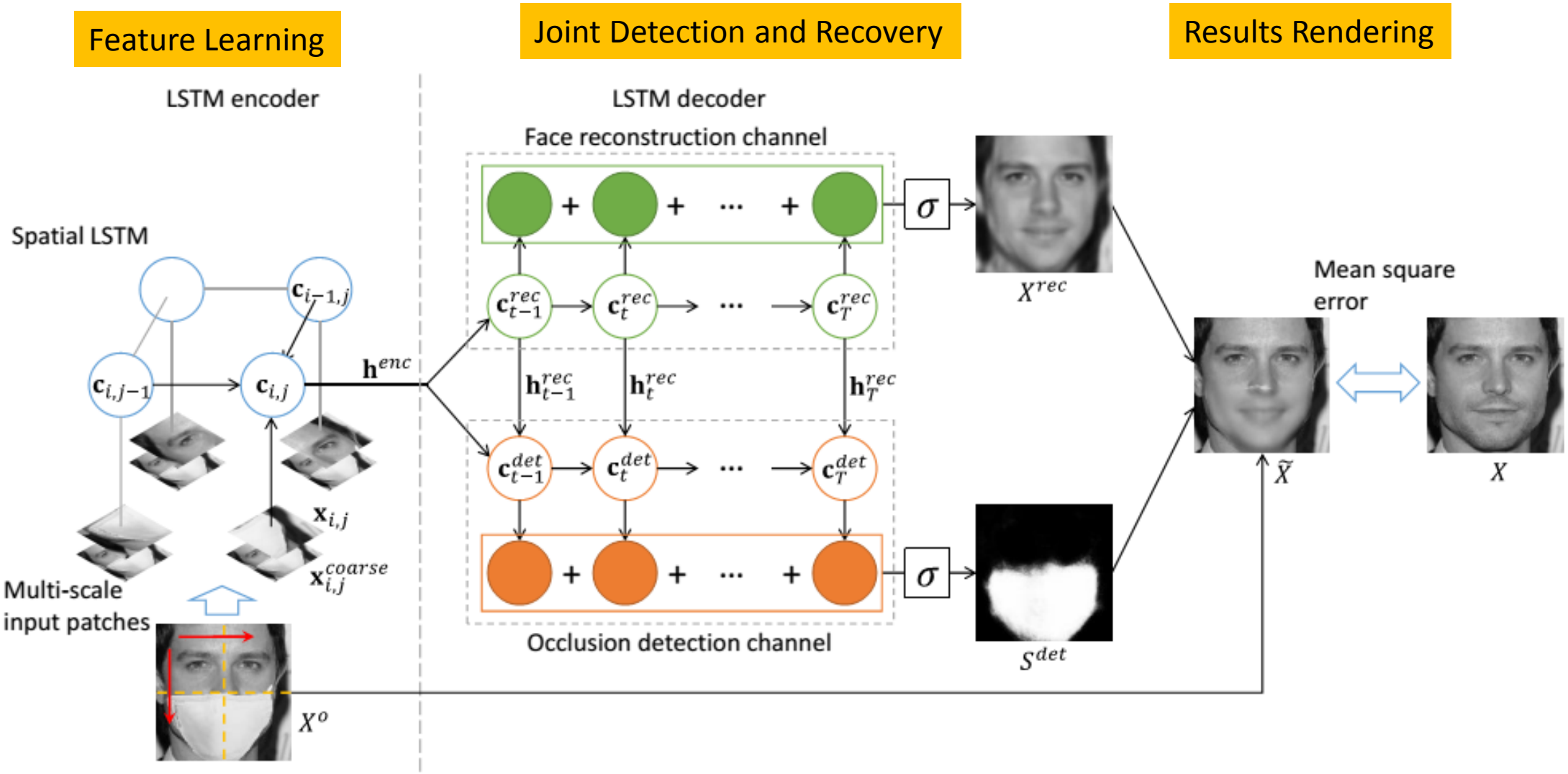
Methods	300-W Dataset		
	Common	Challenging	Full
Zhu et.al [2012]	8.22	18.33	12.0
RCPR [Burgos,2013]	6.18	17.26	8.35
SDM [Xiong,2013]	5.57	15.40	7.50
LBF [Ren,2014]	4.95	11.98	6.32
LBF Fast [Ren,2014]	5.38	15.50	7.37
CFSS [Zhu, 2015]	4.73	9.98	5.76
cGPRT [Lee, 2015]	---	---	5.71
Linkface	4.80	8.60	5.54
Ours (RAR)	4.12	8.35	4.94

Zhu: Face detection, pose estimation, and landmark localization in the wild. CVPR 2012
PCPR: Robust face landmark estimation under occlusion. ICCV 2013
LBF: Face alignment at 3000 fps via regressing local binary features. ECCV 2014
SDM: Supervised descent method and its applications to face alignment. CVPR 2013
CFSS: Face alignment by coarse-to-fine shape searching. CVPR 2015
cGPRT: Face alignment using cascade Gaussian process regression trees. CVPR 2015

Face De-occlusion

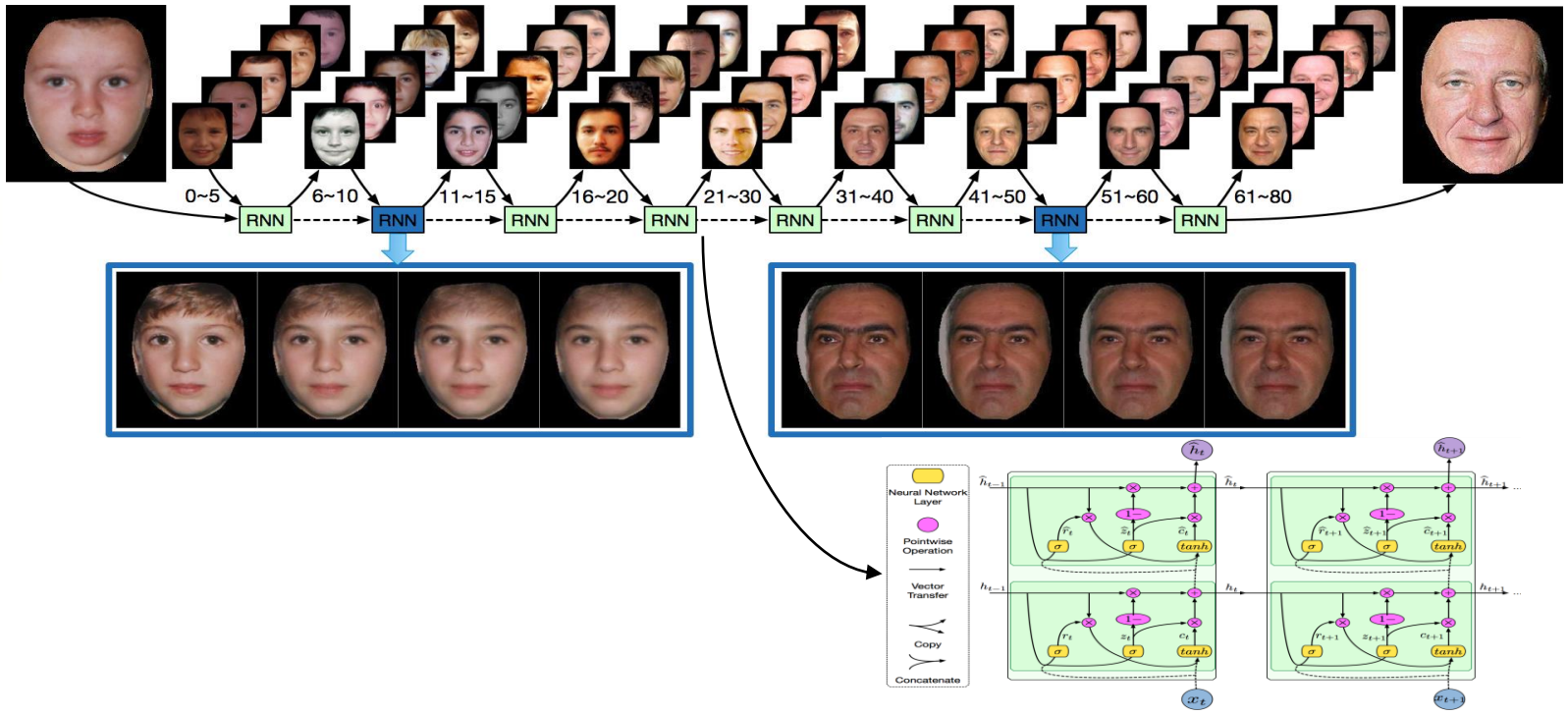


Face De-occlusion Networks



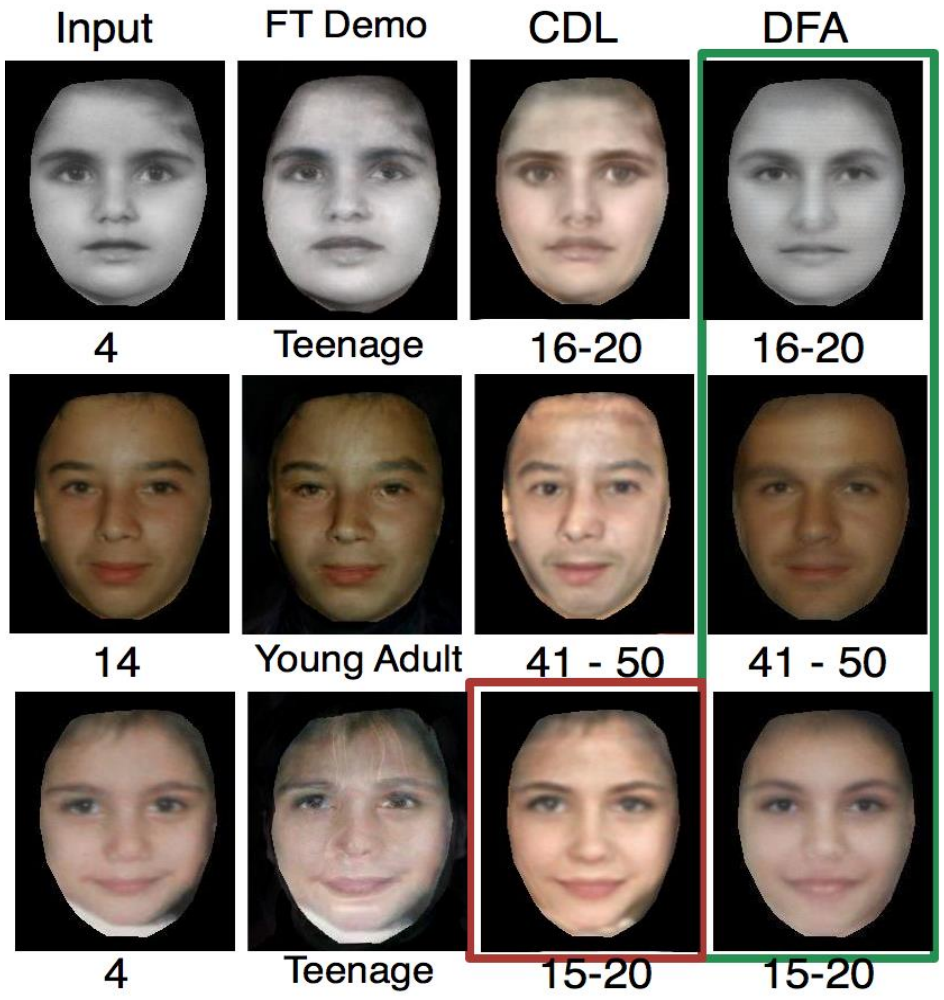
Face De-occlusion Results

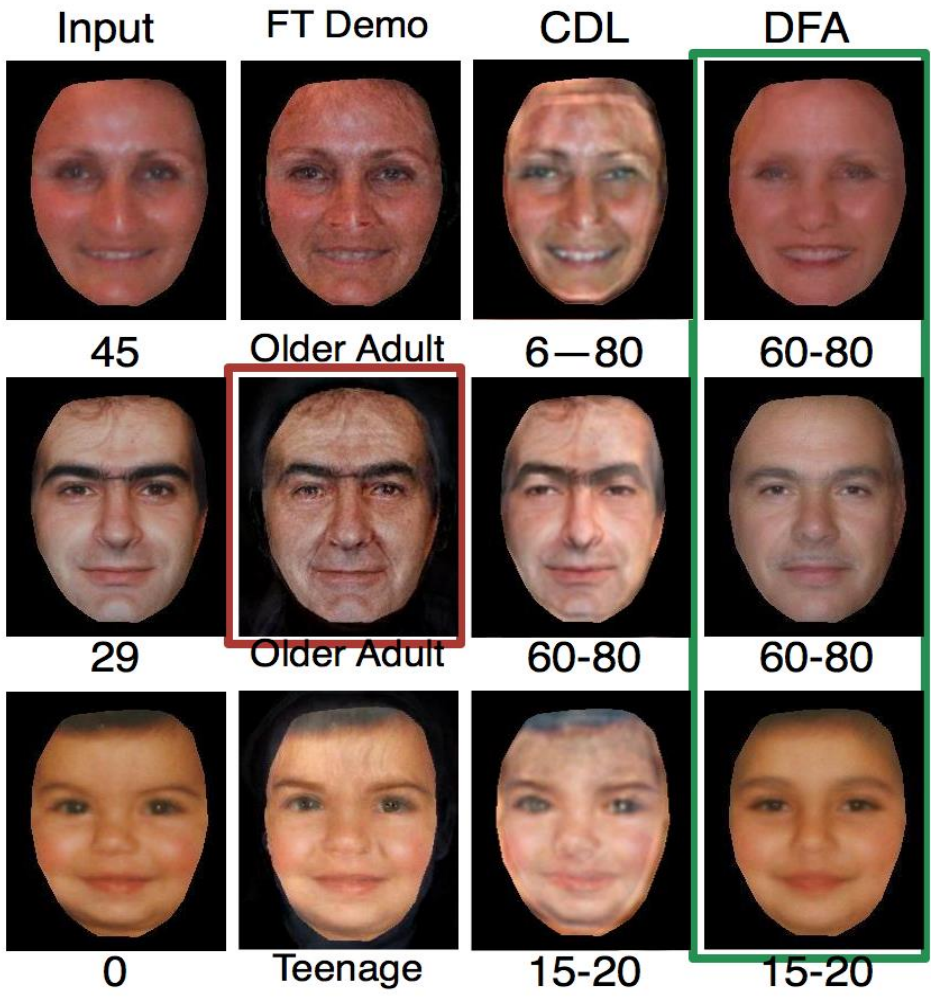
Face Aging Networks



LSTM

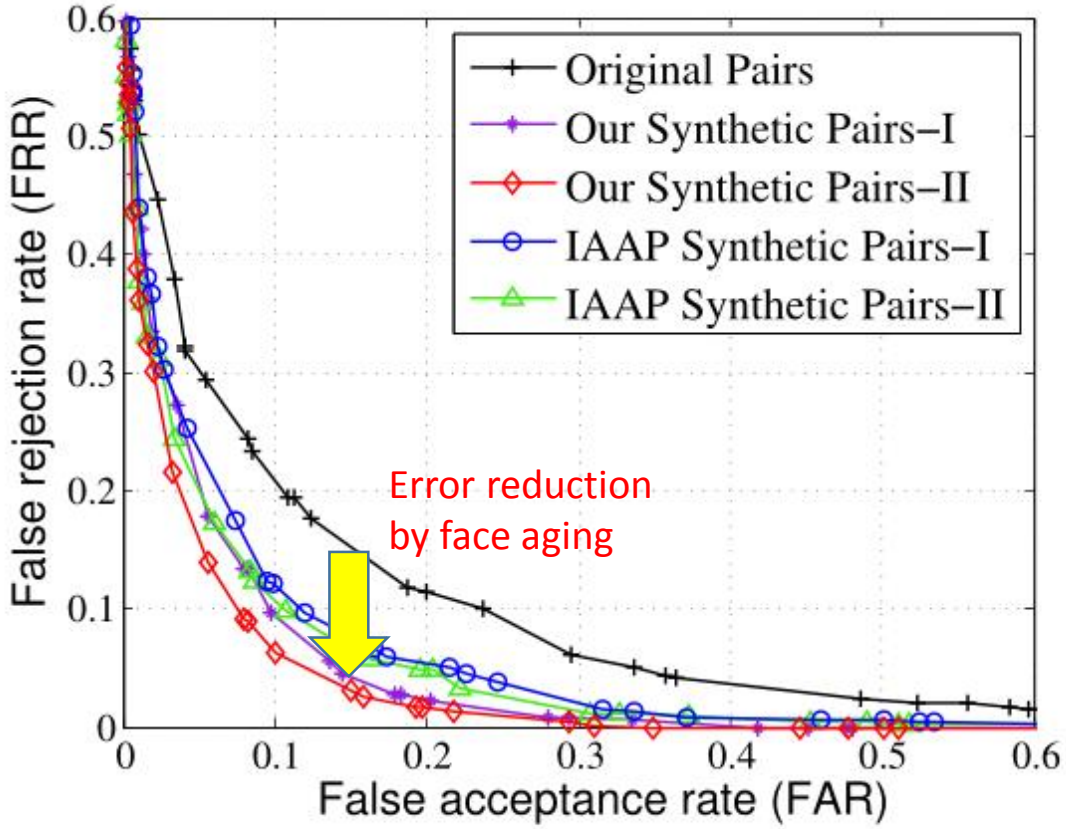
Face Aging Results





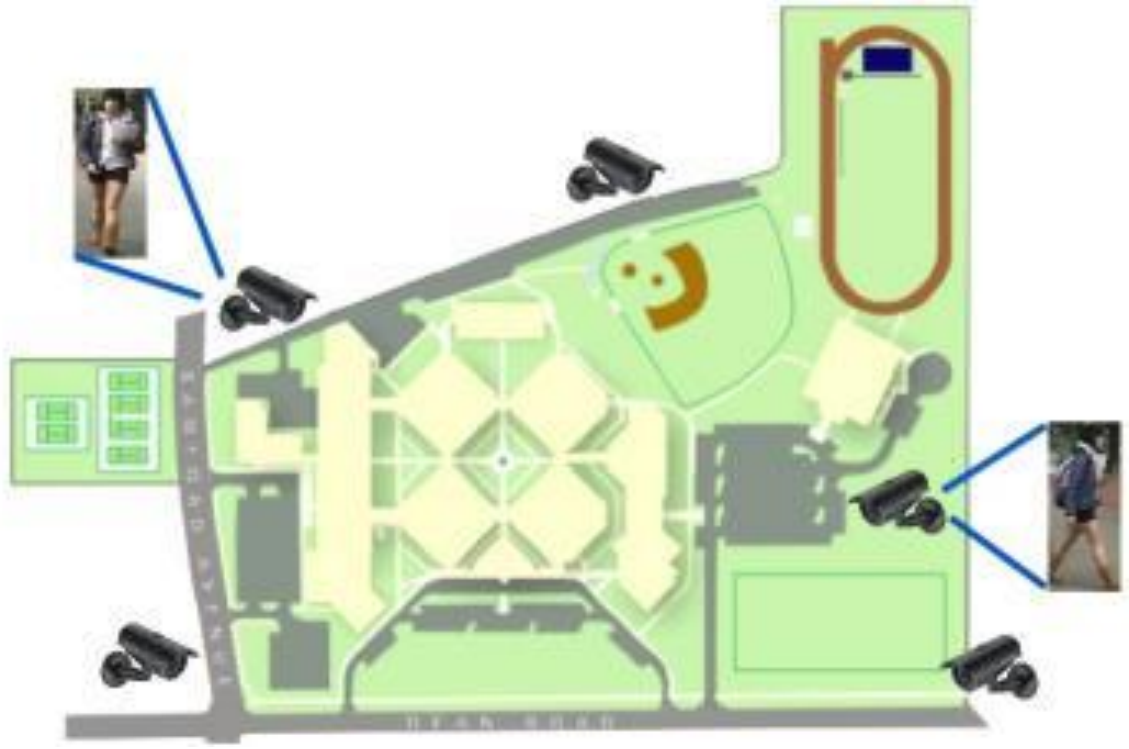
Cross-age Face Verification Results

(a) Pair setting.

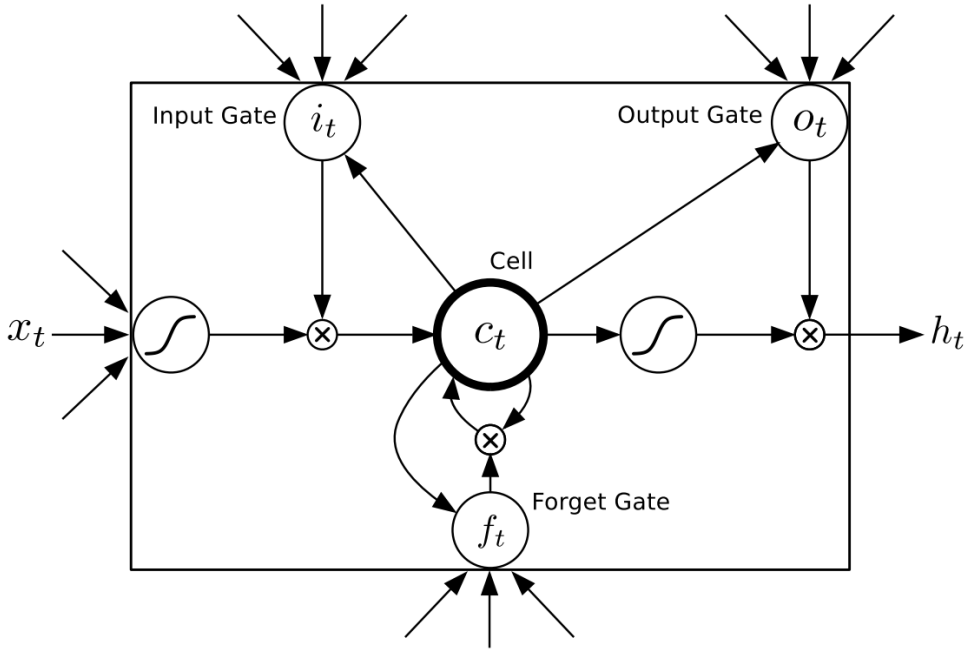


(b) FAR-FRR curve.

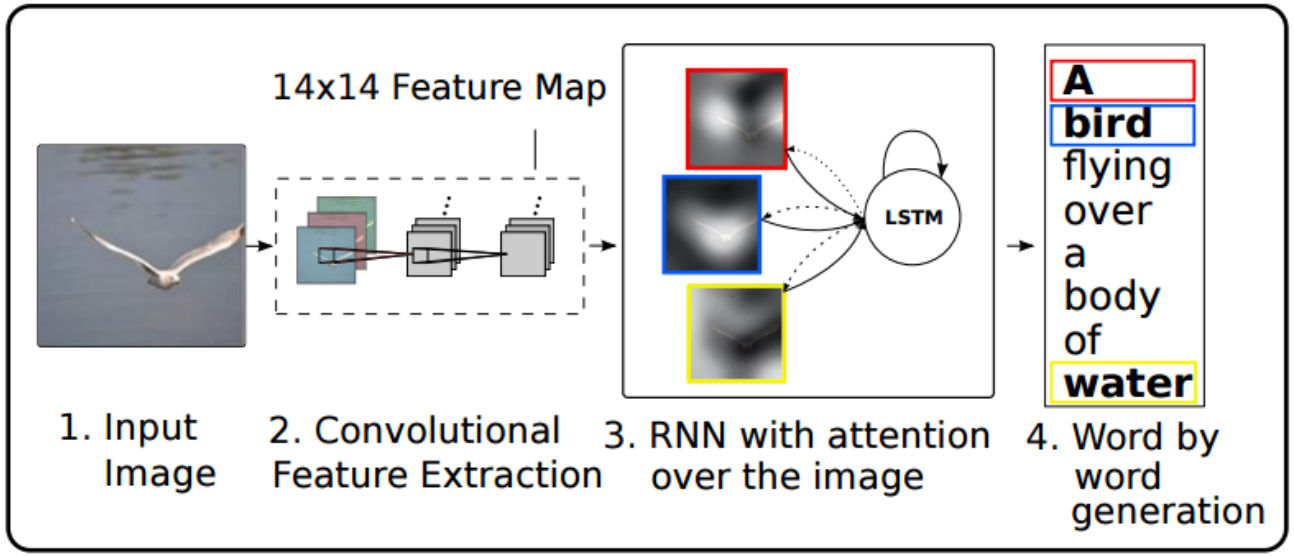
Application III: Human Re-identification



Attention Networks

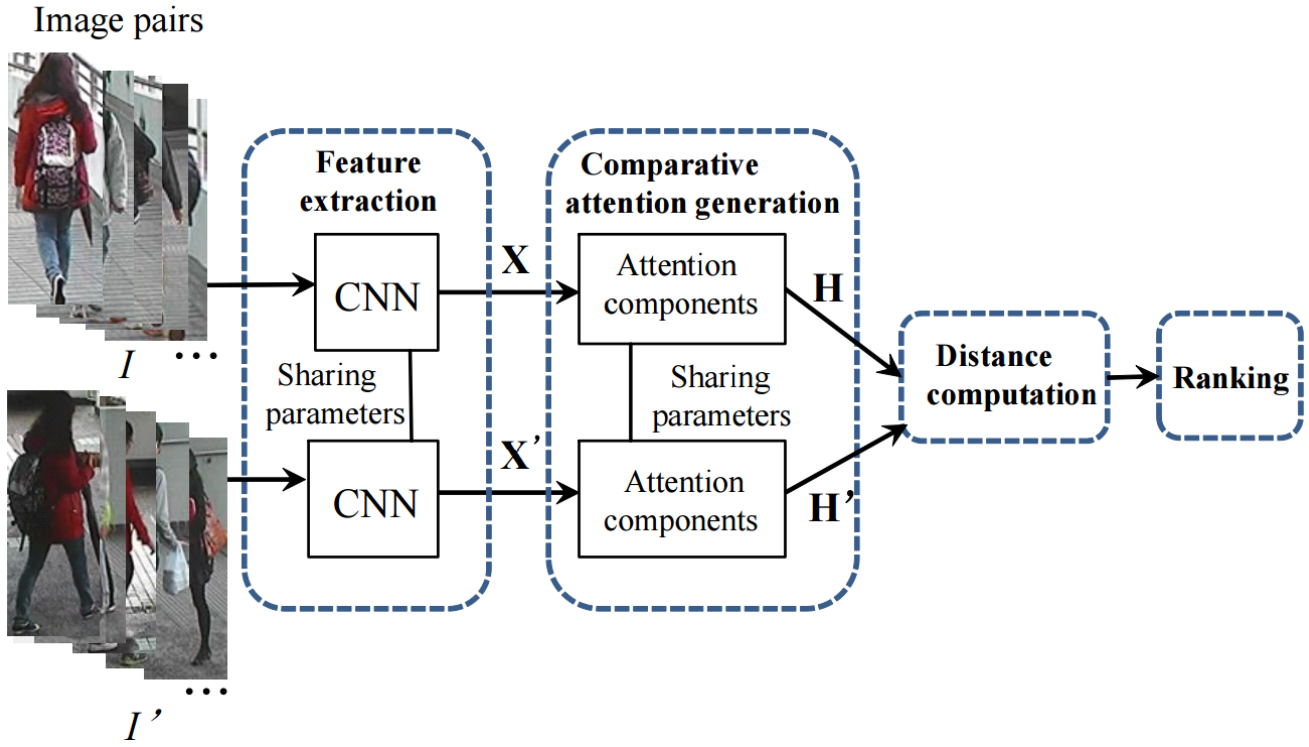


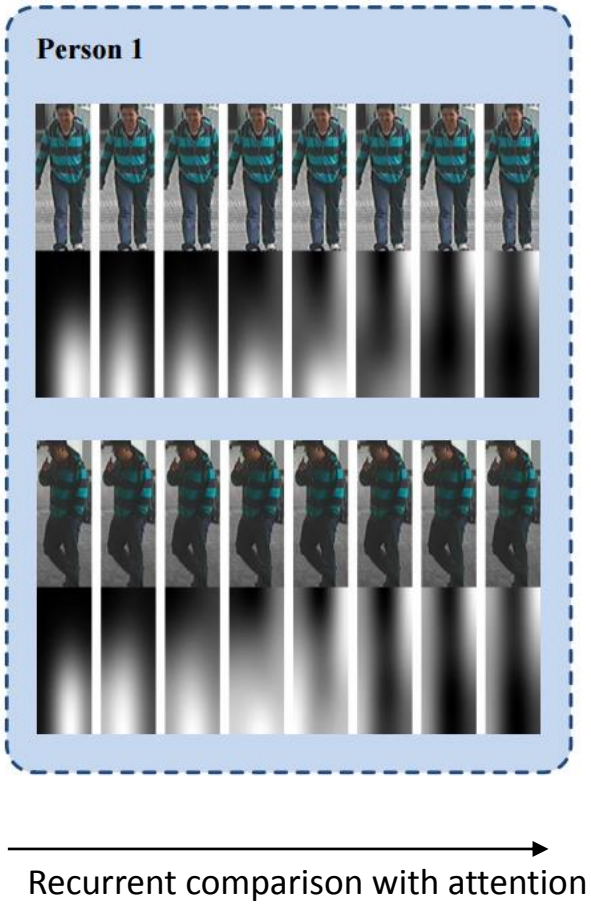
Long Short-Term Memory (LSTM)



Attention Networks

Attentive Comparison Networks





Person Re-ID Results

Results on CUHK01				
Model	Rank1	Rank5	Rank10	CMC
CNN (extra data)	70.45	94.12	98.33	2.11
CNN (CUHK03 pre-train)	70.12	91.33	95.44	2.33
Ours	81	97	1	1.77
SOTA	65.00	89	94	---

Results on CUHK03				
Model	Rank1	Rank5	Rank10	CMC
CNN	52.33	83.02	90.12	3.58
Ours	63	88	93	3.49
SOTA	44.96	77.5	83	---

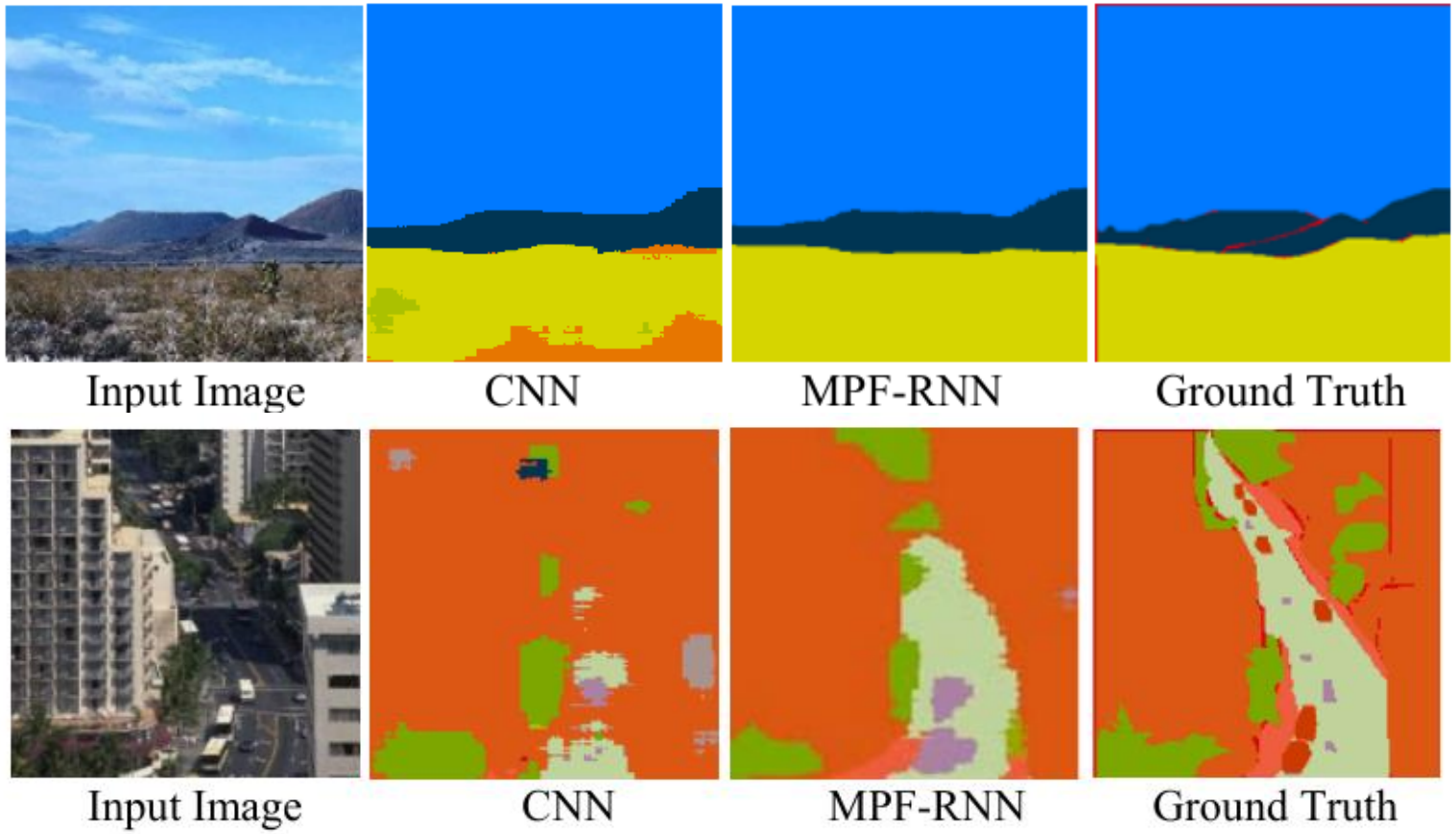
* SOTA = State-of-the-art

Application IV - Scene Understanding

- Predict category label for each pixel.
- Challenging: joint segmentation, classification and detection.

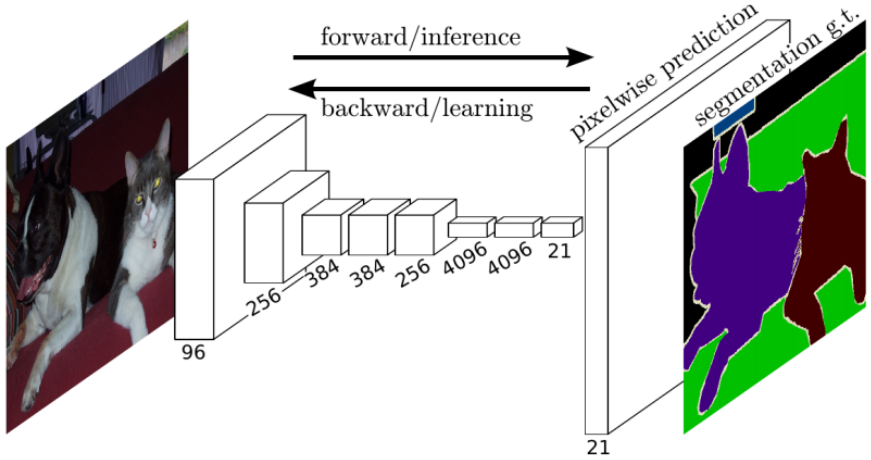
Scene Understanding

- Context is important for distinguishing confusing pixels



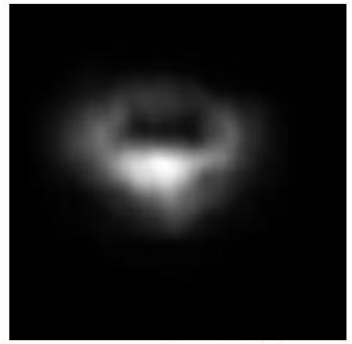
Multi-path Feedback Networks

- Context is important
- However, CNN has limited Receptive Fields even at top layers



A typical CNN model

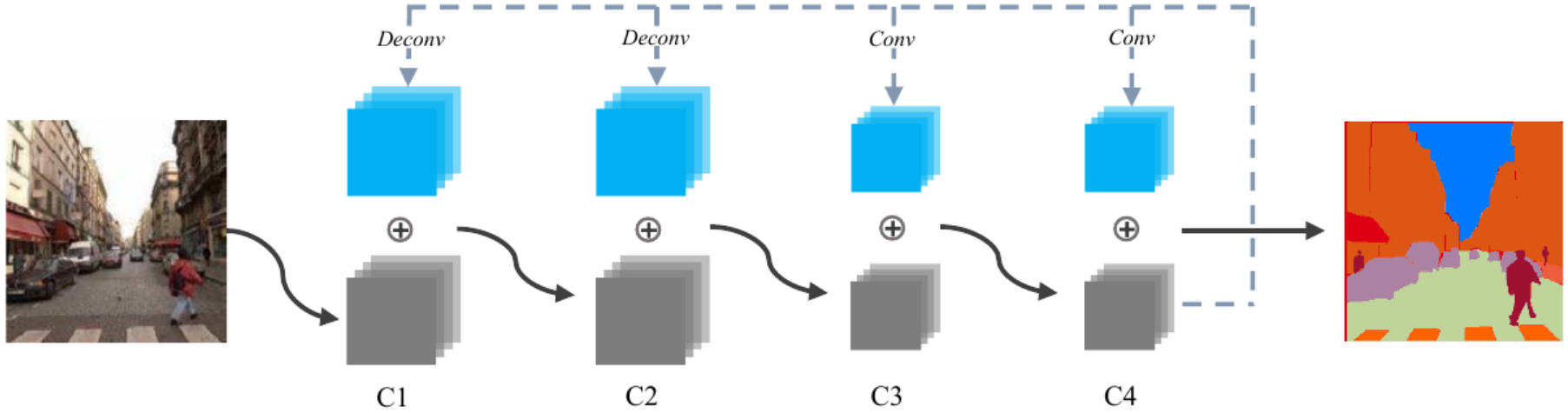
sliding-window stimuli



receptive field

Multi-path Feedback Networks

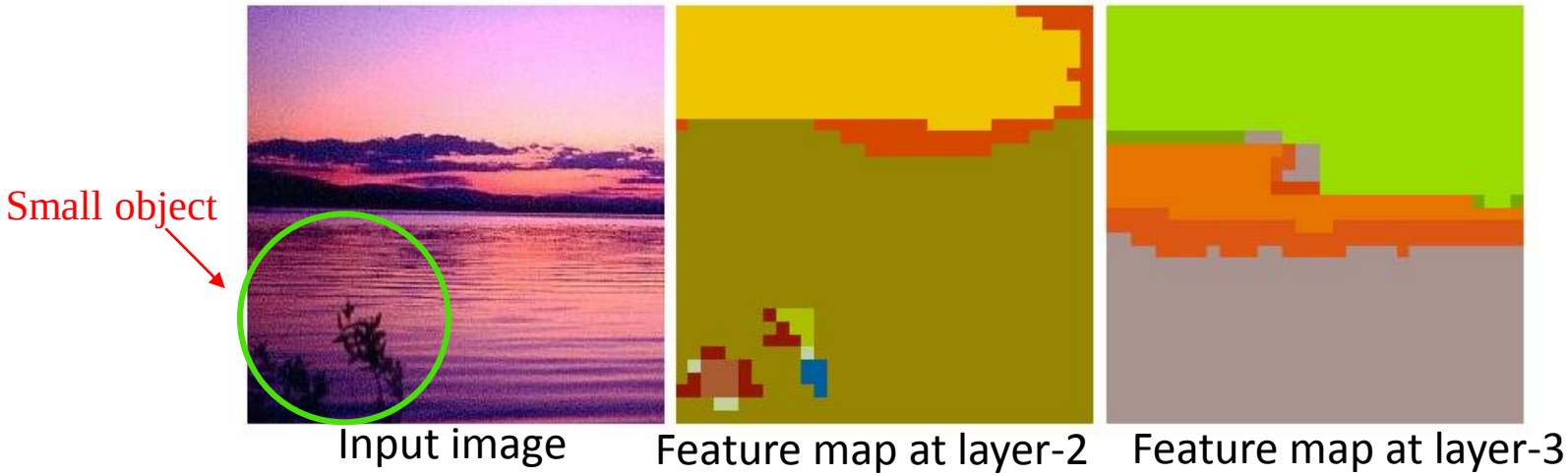
- Architecture



- Multi-path feedback: propagate context information at top layers to multiple bottom layers
- Multi-step fusion: aggregate results from multiple steps to parse small objects better

Multi-path Feedback Networks

- Multi-step Loss
  - Output features capturing context from smaller RF
  - More discriminative for small objects

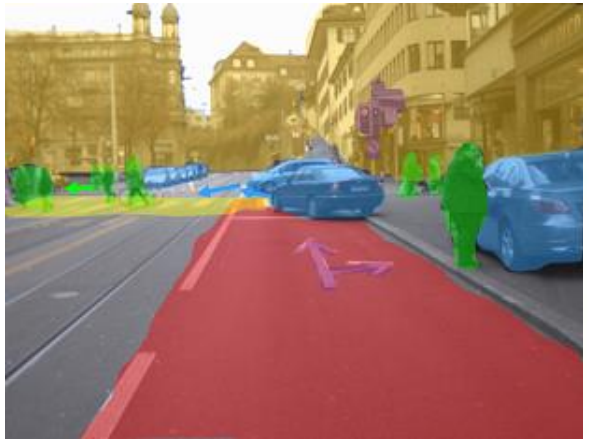


Scene Parsing Results

*SIFTFLOW Dataset

+Dag-recurrent neural networks for scene labeling. ArXiv 2015

Conclusions



- Deep learning (deep neural networks) is revolutionizing visual signals processing.
- Big visual data is very valuable.
- Computational resource is important.

NUS National University of Singapore

Thanks!

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