DualBox: Generating BBox Pair with Strong Correspondence via Occlusion Pattern Clustering and Proposal Refinement

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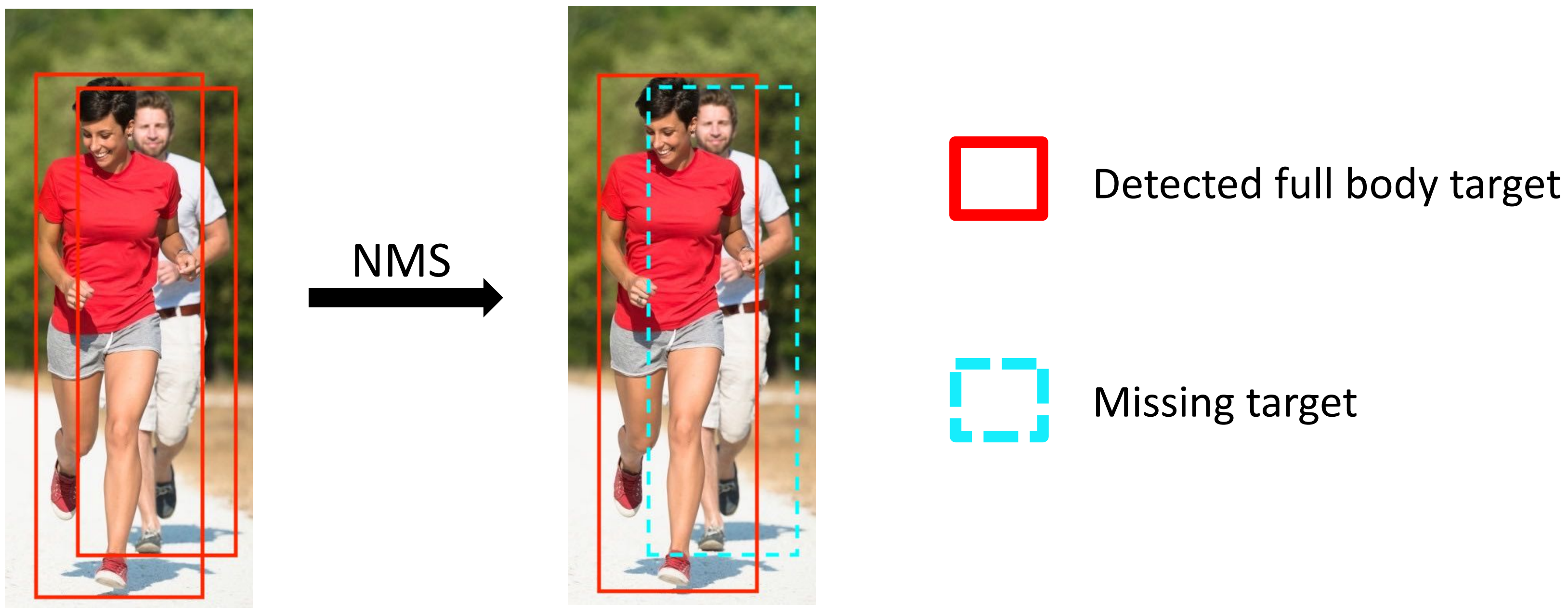
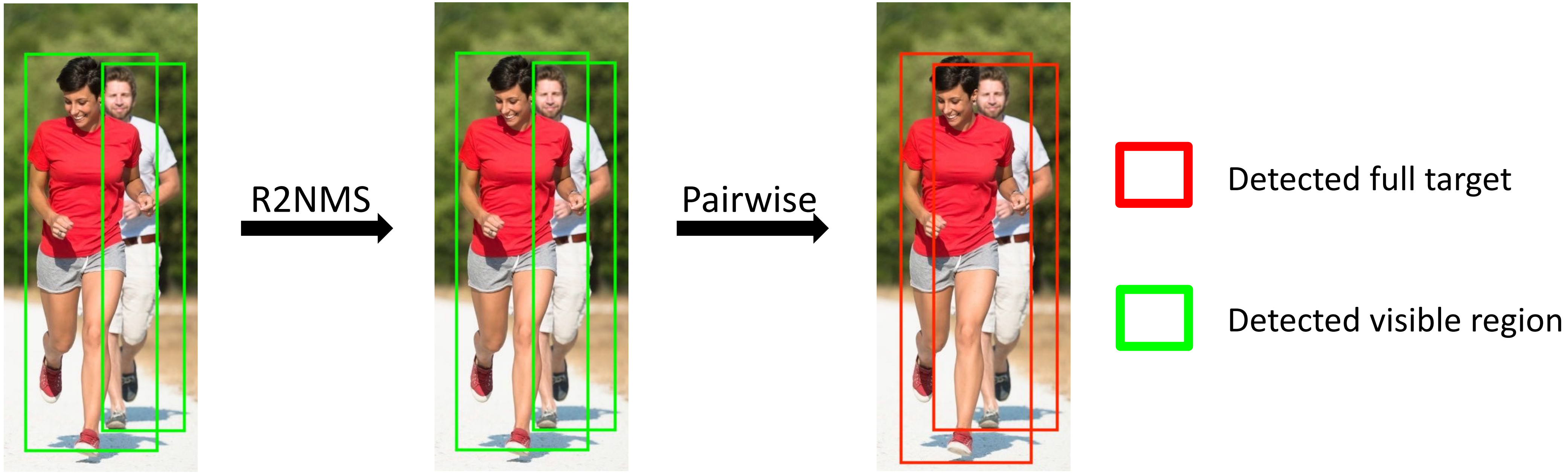
Introduction



NMS result: under heavily occluded condition, some true positives are wrongly suppressed.

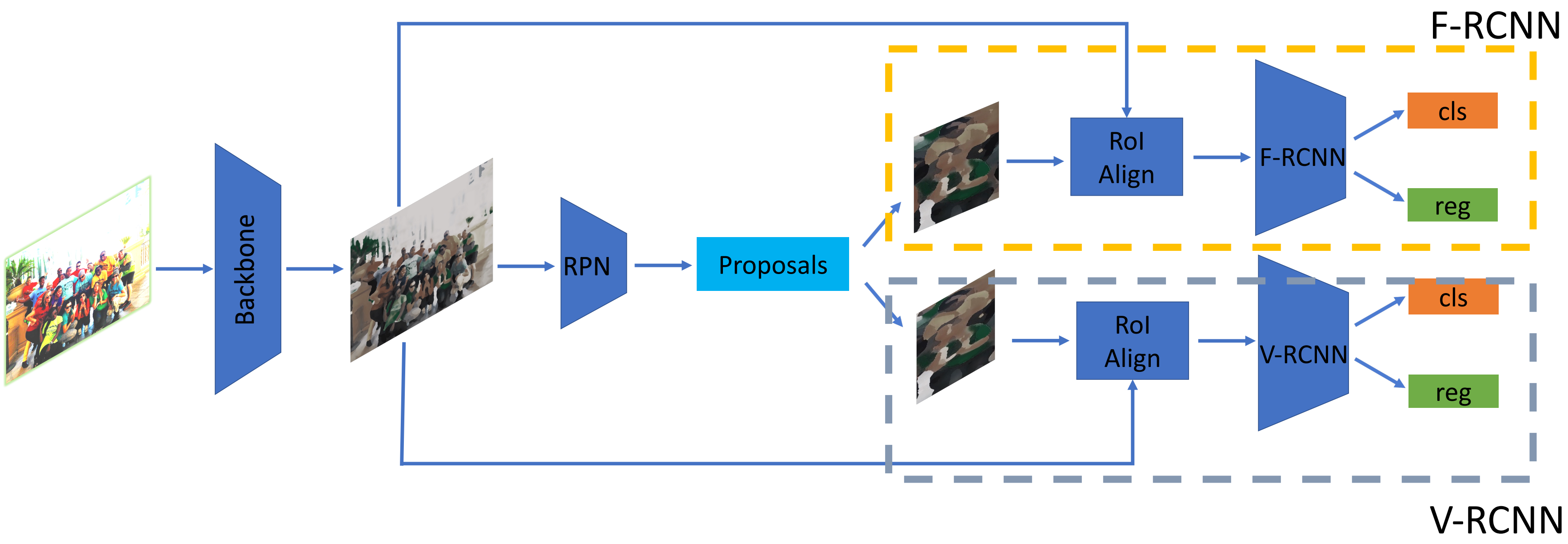
R2NMS[1]



R2NMS result: use visible region BBoxes to calculate IoU and do NMS. Then replace them with the pairwise full body BBoxes.

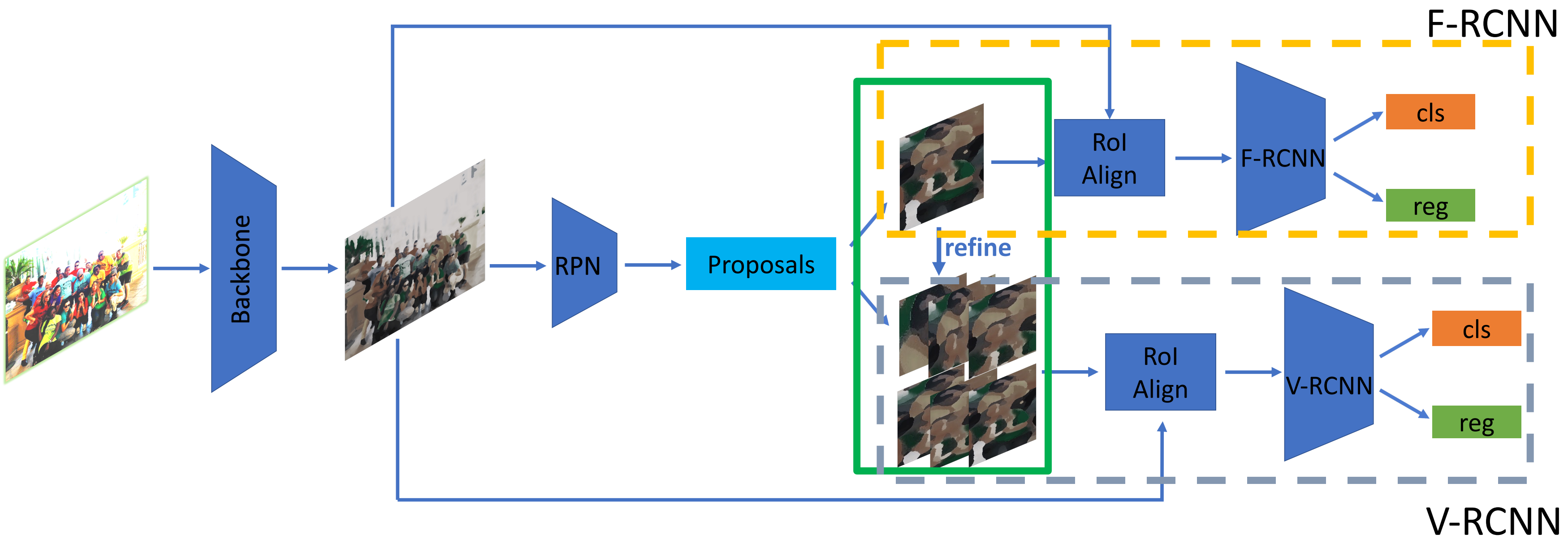
[1] X. Huang, Z. Ge, Z. Jie, and O. Yoshie, “Nms by representative region: Towards crowded pedestrian detection by proposal pairing,” in *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 2020, pp. 10 750–10 759.

DualBox ---- Fundemental architecture



FV-RCNN architecture

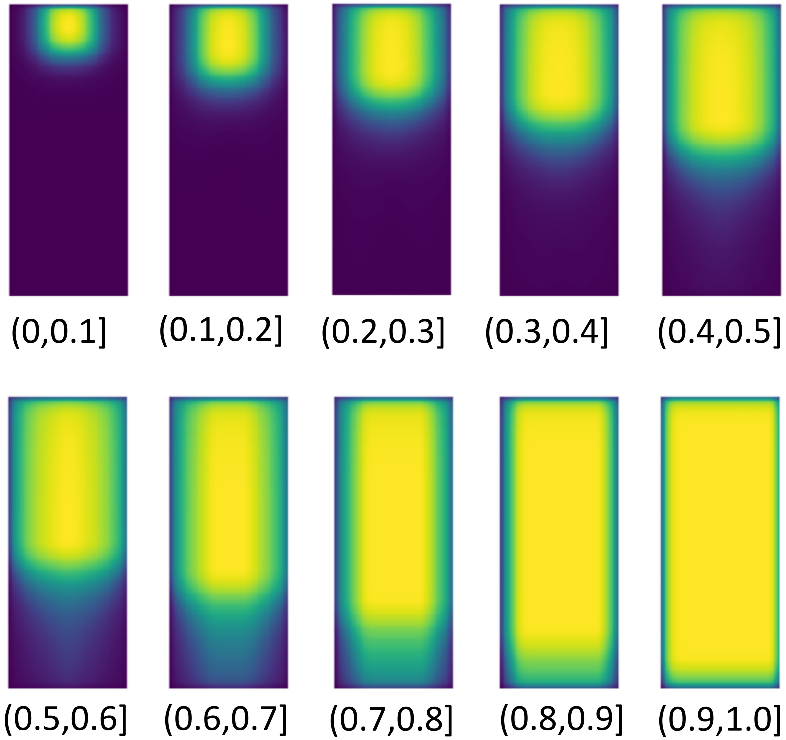
DualBox ---- Assigning strategy



Refine FV-RCNN architecture

Several occlusion patterns are adpoted on each full body proposal to refine the full body proposals into visible body proposals without complex assigning strategies.

DualBox ---- Occlusion patterns



Distribution of occlusion patterns under different degrees of visibility

Full body box $\xrightarrow{\text{V-ratio}}$ **Visible region box**

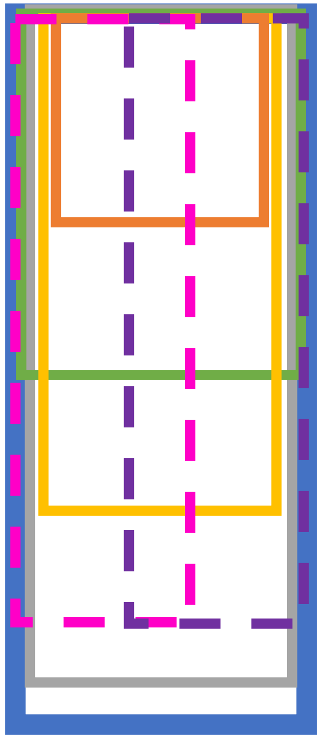
DualBox ---- Occlusion patterns

Different candidate occlusion patterns are implemented on all the full body annotations.

Calculate the IoU between new boxes and original visible body annotations.

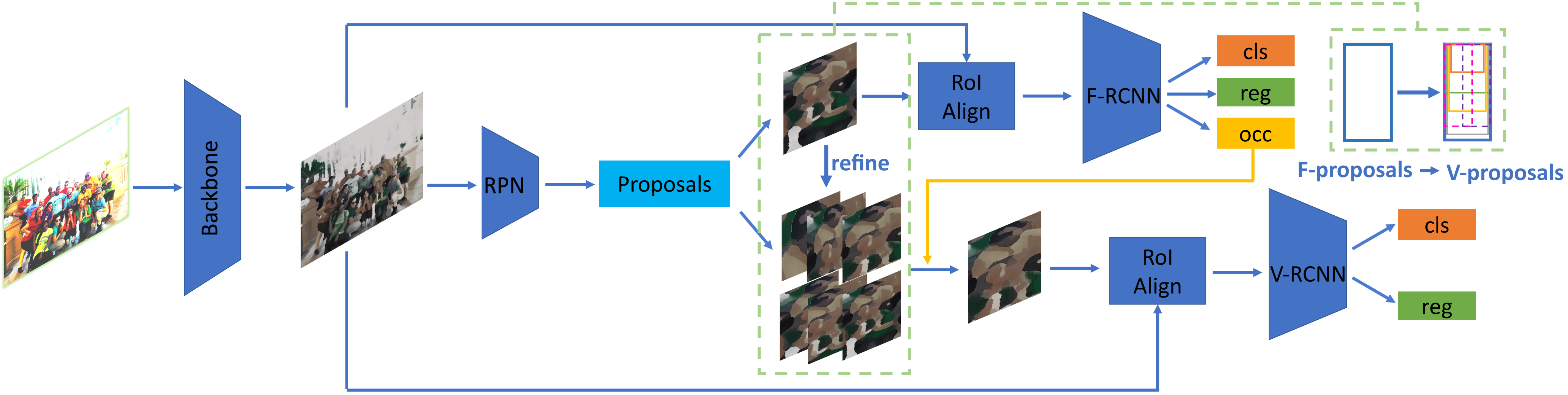
If IoU > 0.5: match
Otherwise: not match

matching rate = # matching boxes / # total boxes



9.9% Head
32.8% Half body
85.9% Most half body
80.1% Almost full body
69.8% Left body
24.8% Right body

DualBox ---- Occlusion branch and final architecture



DualBox architecture

Experiments on CrowdHuman[2]

Method	MR_V	MR	AP	Recall	ΔMR_V	ΔMR
Baseline	55.94	50.42	84.95	90.24		
Baseline*	54.67	47.64	83.79	87.86		
FV-RCNN	55.41	46.32	84.62	88.35		+1.32
Refine FV-RCNN	53.61	46.55	84.74	88.36	+1.06	+1.09
DualBox	**53.25**	**45.65**	84.82	88.38	**+1.42**	**+1.99**

Experimental results on CrowdHuman

[2] S. Shao, Z. Zhao, B. Li, T. Xiao, G. Yu, X. Zhang, and J. Sun, "Crowdhuman: A benchmark for detecting human in a crowd," *arXiv preprint arXiv:1805.00123*, 2018.

Experiments on CityPersons[3]

Methods	R^2NMS	Joint NMS	**R**	**HO**
Baseline (MGAN)			13.8	57.0
Baseline*			13.7	58.3
DualBox			11.5	54.7
DualBox	✓		11.4	54.2
DualBox		✓	11.4	54.3

Experimental results on CityPersons

[3] S. Zhang, R. Benenson, and B. Schiele, "Citypersons: A diverse dataset for pedestrian detection," in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 2017, pp. 3213–3221.

Ablation study

Method	parallel	cascade	MR_V	MR	AP	Recall
Baseline*			54.67	47.64	83.79	87.86
FV-RCNN	√		55.41	46.32	84.62	88.35
		√	58.84	46.39	84.62	88.74
refine FV-RCNN	√		53.61	46.55	84.74	88.36
		√	53.47	46.59	84.59	88.55
DualBox	√		53.25	**45.65**	84.82	88.38
		√	**53.21**	46.11	84.87	88.39

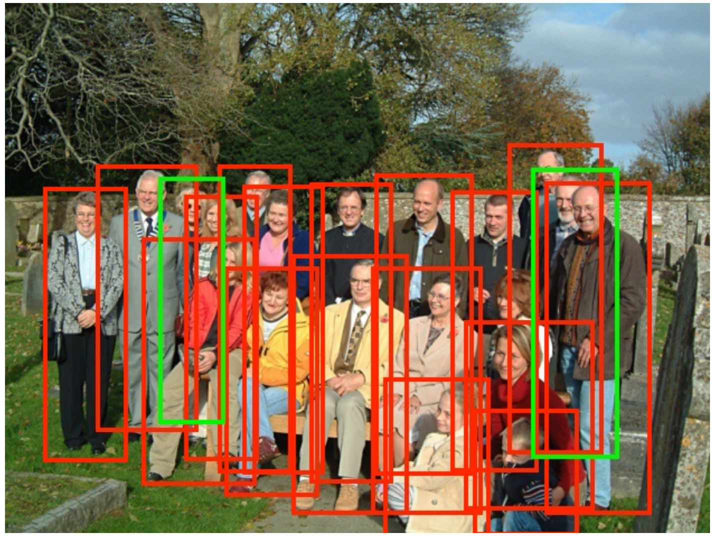
Ablation study about parallel and cascade refinement mode on CrowdHuman

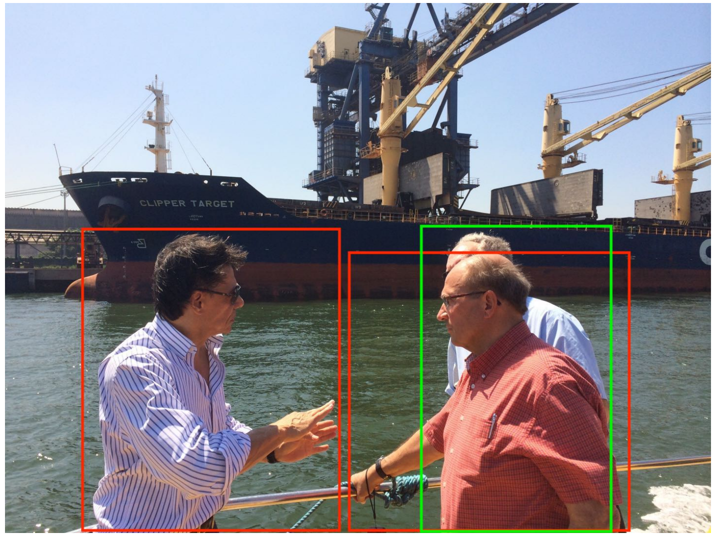
Method	MR	AP	Recall
NMS	45.65	84.82	88.38
R^2NMS	45.34	86.27	91.33

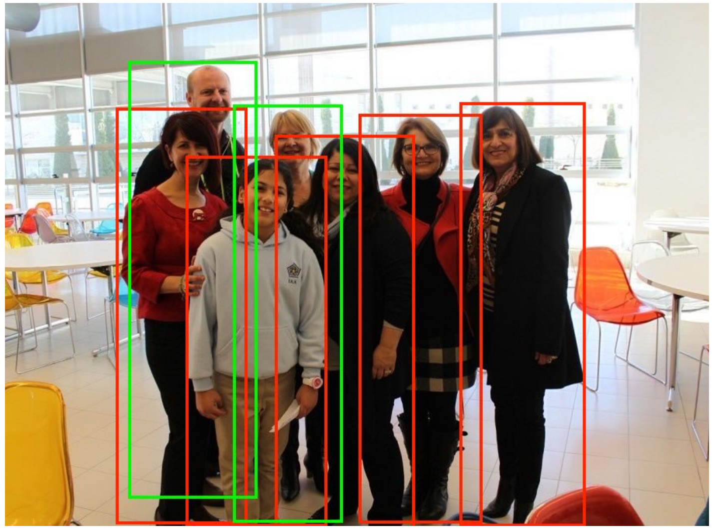
Ablation study about post processing approaches on CrowdHuman

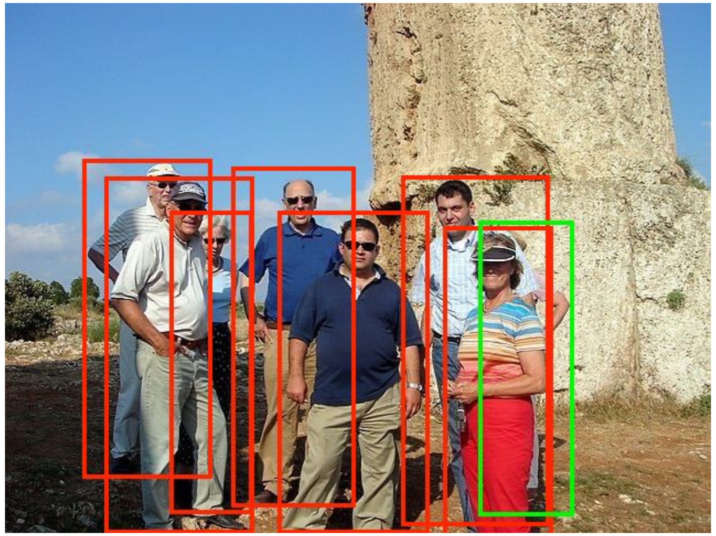
[3] S. Zhang, R. Benenson, and B. Schiele, "Citypersons: A diverse dataset for pedestrian detection," in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 2017, pp. 3213–3221.

Visulization results









Detected results of baseline Faster R-CNN

Extra detected results of our DualBox

Thanks for listening