Efficient Object Detection in Large Images Using Deep Reinforcement Learning

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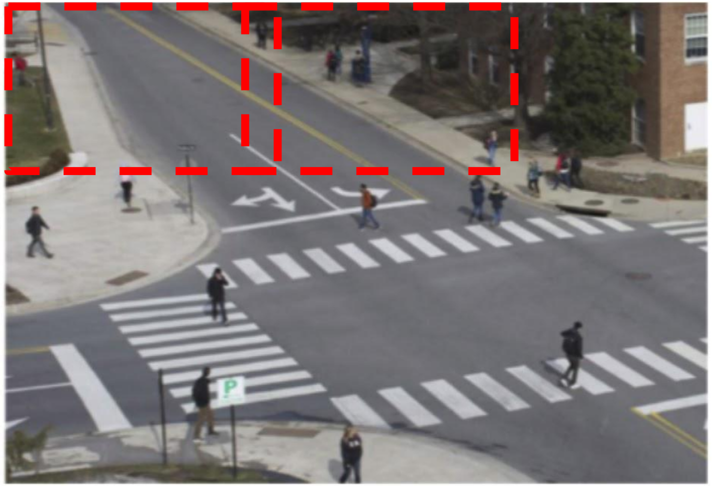
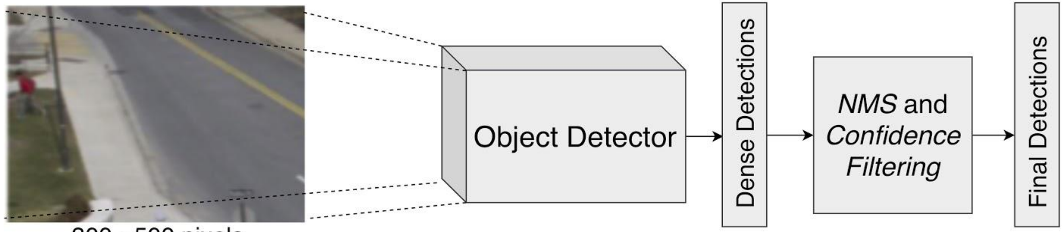
Detection in Large Images - Sliding Window

- No need to downsample
- Low memory requirement
- Large runtime to process each window



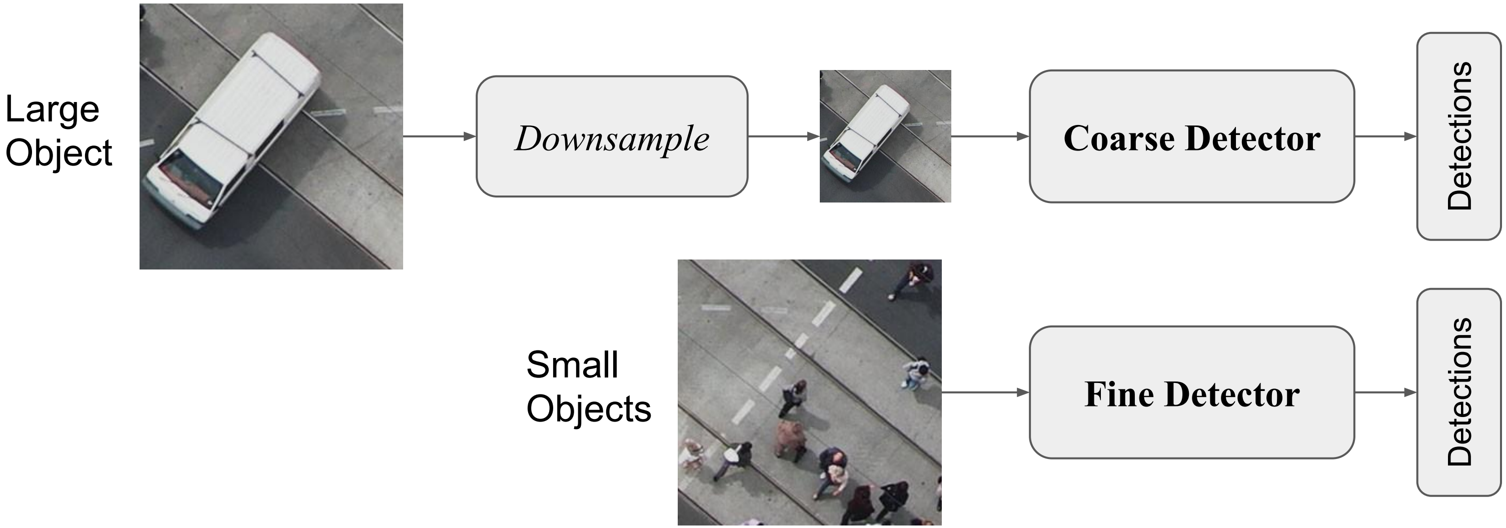
>1000 pixels

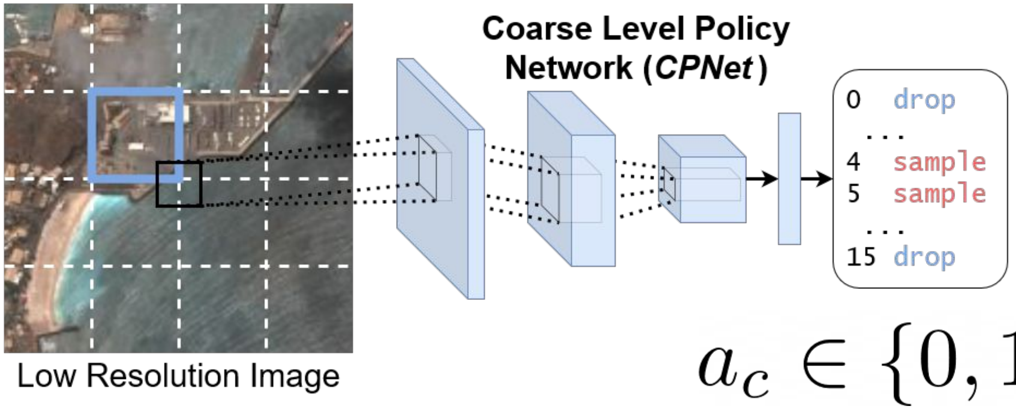


300 - 500 pixels

Proposed Method - Adaptive Sliding Window

Small objects requires fine-level information whereas large objects can be detected at coarse-level.



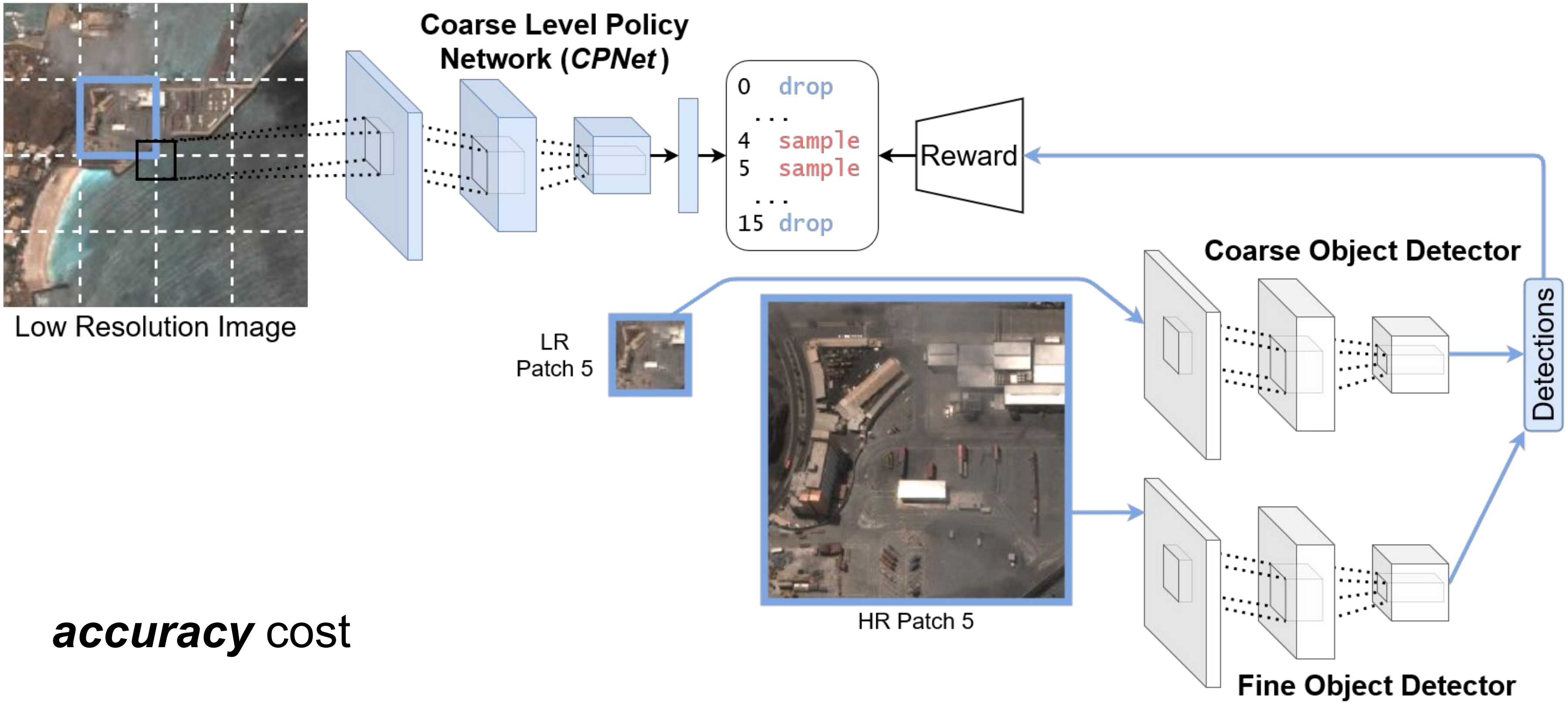


$$a_c \in \{0, 1\}^{P_c}$$

Policy network treats sampling each image patch as a Bernoulli random variable

$$\pi_c(a_c | x_L, \theta_p^c) = \prod_{i=1}^{P_c} (s_c^i)^{a_c^i} (1 - s_c^i)^{(1 - a_c^i)}$$

$$s_c = f_p^c(x_L; \theta_p^c)$$



accuracy cost

$$R_{acc} = \sum_{i=1}^{P_c} \left(Recall\left(\hat{Y}_i^f, Y_i\right) - \left(Recall\left(\hat{Y}_i^c, Y_i\right) + \beta \right) \right) \cdot N_i$$

Modeling the Policy Networks

Policy network treats sampling each image patch as a Bernoulli variable

$$\pi_c(a_c|x_L, \theta_p^c) = \prod_{i=1}^{P_c} (s_c^i)^{a_c^i} (1 - s_c^i)^{(1-a_c^i)}$$

$$s_c = f_p^c(x_L; \theta_p^c)$$

Policy network is trained with policy gradient method, with advantage function

$$J_c = \mathbb{E}\left[R_c(a_c, a_d, Y)\right]$$

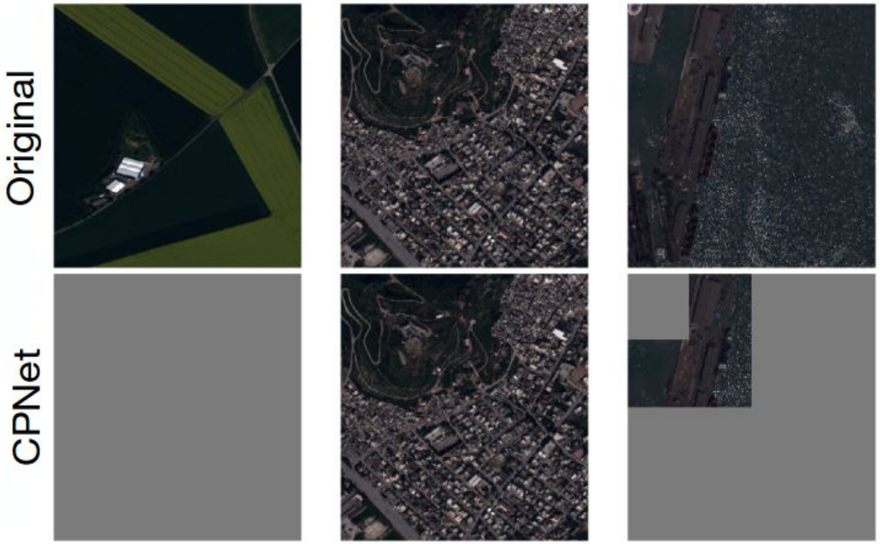
$$\nabla_{\theta_p^c} J_c = \mathbb{E}\left[R_c \cdot \nabla_{\theta_p^c} \log \pi_{\theta_p^c}(a_c|x_L)\right]$$

Experiments - xView

Experiments on the xView dataset, consisting of 847 very large images (***>3000*** x ***>3000*** px).

Model/Metric	HR	AP	AR	Run-time	HR
Random (5×)	50	24.1	47.1	1408	31
Entropy (5×)	50	25.4	47.2	1415	31
Sliding Window-L (5×)	0	26.3	39.8	640	0
Sliding Window-H	100	39.0	60.9	3200	100
Gao et al. [7] (5×)	35.4	35.2	55.5	1551	31.6
Ours (5×)	35.5	38.1	59.7	1484	31.5

Table 1 : Results on the xView test set.



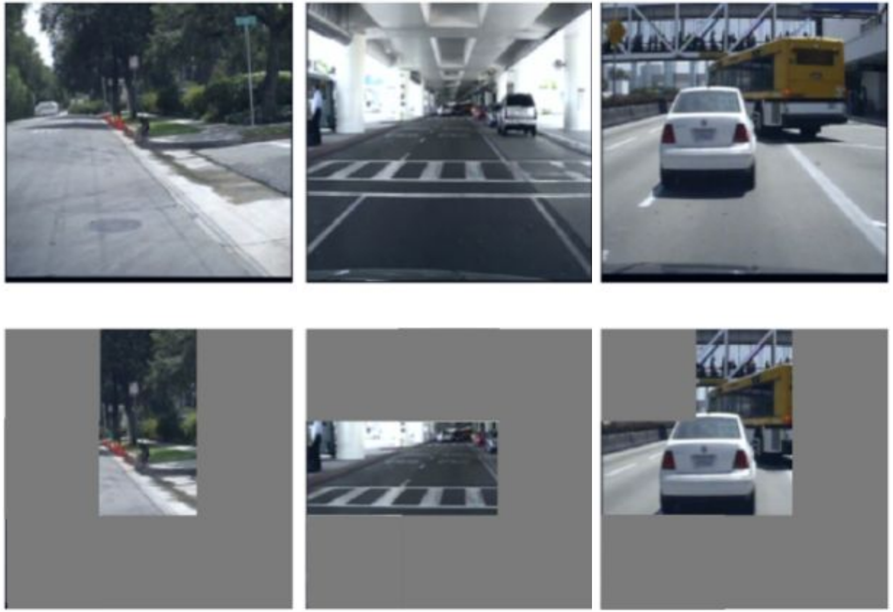
Gao, Mingfei, Ruichi Yu, Ang Li, Vlad I. Morariu, and Larry S. Davis. "Dynamic zoom-in network for fast object detection in large images." In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pp. 6926-6935. 2018.

Experiments - Caltech Pedestrian

Experiments on the Caltech Pedestrian dataset (***>800*** x ***>800*** px).

Model/Metric	AP	AR	Run-time	HR
Random (×5)	30.9	62.1	248	44.4
Entropy (×5)	34.0	63.9	250	44.4
Sliding Window-L (×5)	21.2	46.3	90	0
Sliding Window-H	64.7	74.7	450	100
Gao et al. [7] (×2)	64.5	73.1	295	7.1
Gao et al. [7] (×5)	57.3	70.7	309	43.3
CPNet (×2)	64.4	74.5	267	6.6
CPNet (×5)	61.7	74.1	270	44.4

Table 2 : Results on the Caltech Pedestrian test set.



Code

https://github.com/uzkent/EfficientObjectDetection