An Integrated Framework for Pedestrian Tracking

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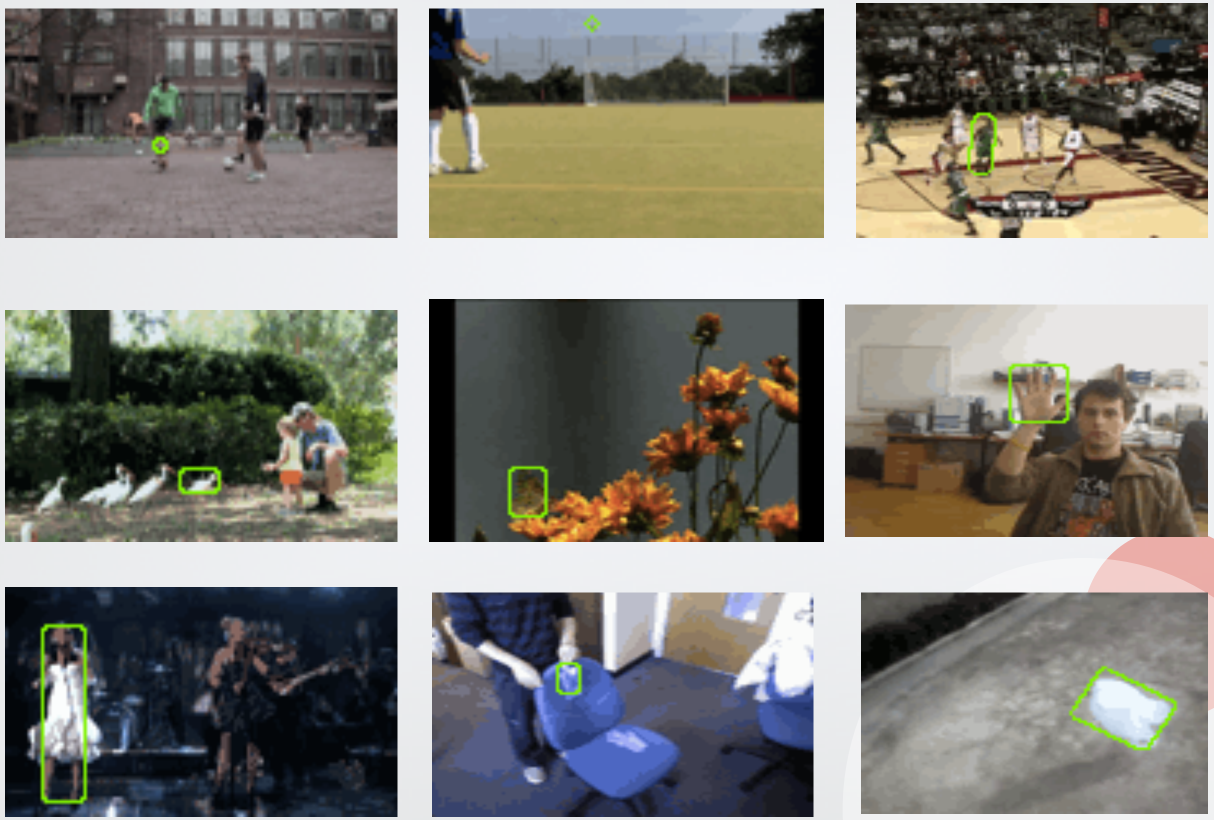
Why Pedestrian Tracking?

General Object Tracking

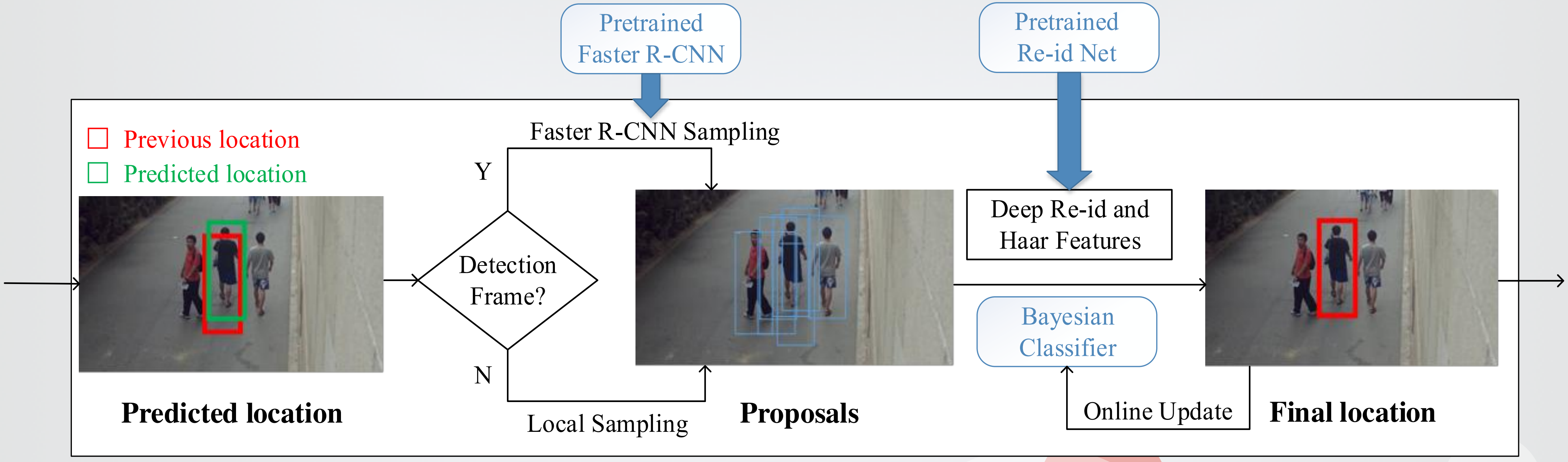


VOT Challenges

Pedestrian Tracking

1. Various gestures, appearances and poses
2. Distraction from similar person
3. Complete occlusion

The ILFPT Model Overview



Frame *t*

Target Prediction

Assume that we are tracking on frame t, the speed of the target in the current frame can be estimated by

$$v_x^t = \rho v_x^t + (1-\rho)\Delta_x^{t-1},$$
$$v_y^t = \rho v_y^{t-1} + (1 - \rho)\Delta_y^{t-1}$$

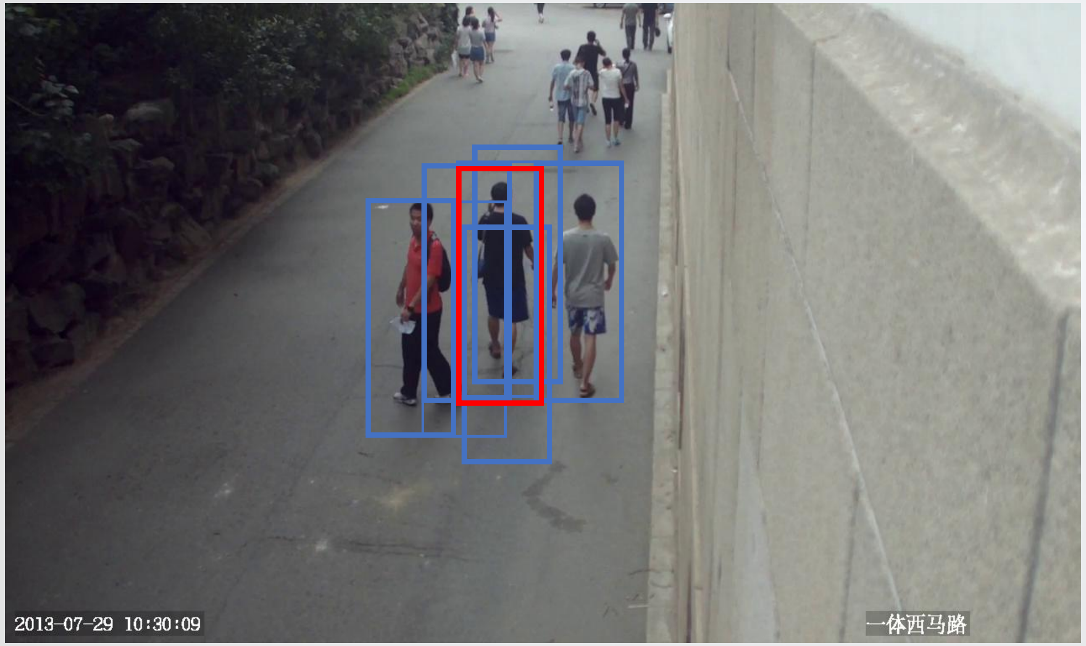
where v_x^{t-1} and v_y^{t-1} are respectively the horizontal and vertical speed in frame $t-1$, $\rho \in [0,1]$ is the momentum factor that controls the weights of the previous speed and $\Delta_x^{t-1} = x^{t-1} - x^{t-2}, \Delta_y^{t-1} = y^{t-1} - y^{t-2}$

Therefore, the center of tracking window in frame t can be predicted as

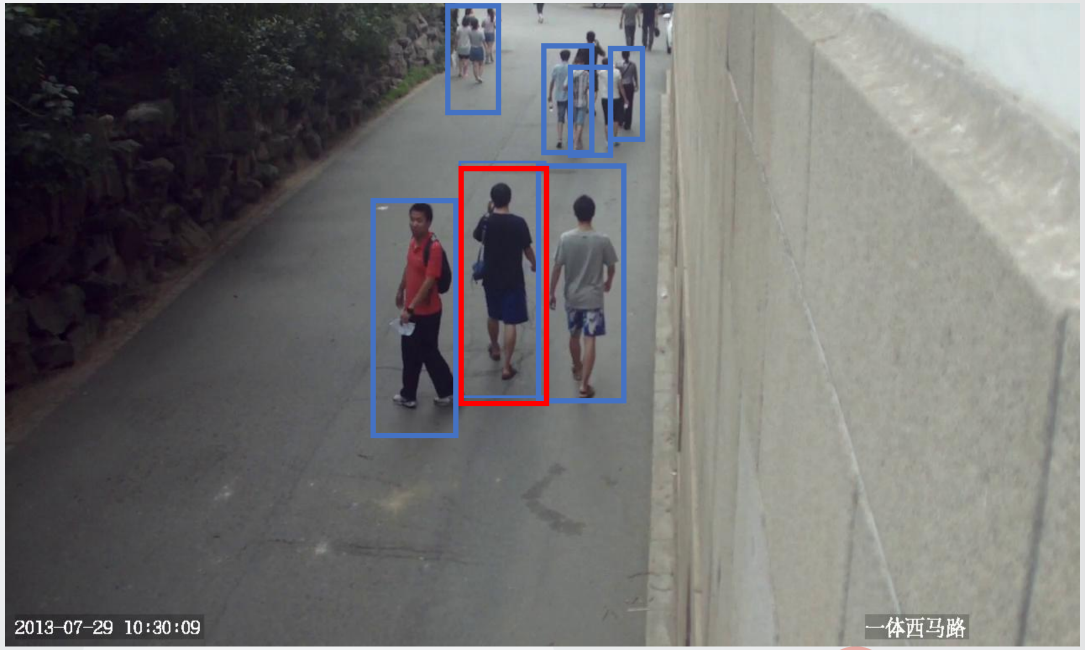
$$x^t = x^{t-1} + v_x^t$$
$$y^t = y^{t-1} + v_y^t$$

Two Sampling Techniques

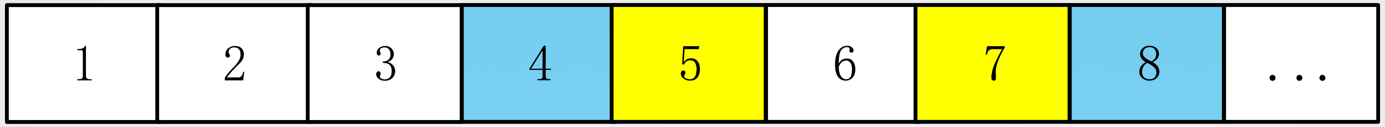
Local sampling



Faster RCNN sampling



Detection Frames & Non-detection Frames



Detection Frames

- Periodical Frames
- Feed-back Frames

Non-detection Frames

1. Faster RCNN sampling is activated in detection frames.
2. Faster RCNN sampling helps adapt the bounding box size.
3. Switching scheme improves speed.

Online Learning Model

A positive sample set $\mathcal{S}^+$ and a negative sample set $\mathcal{S}^-$ are initialized for storing new pedestrian patterns and updating online model. For each candidate sample c, we obtain a compressed low-dimensional feature $\mathbf{v} = (v_1, v_2, \dots, v_n)^T \in \mathbb{R}^n$.

$$R(\boldsymbol{v}) = \log \frac{p(y=1|\mathbf{v})\}}{p(y=0|\mathbf{v})\}} = \sum_{i=1}^{n} \log \frac{p(v_i|y=1)}{p(v_i|y=0)}$$

The conditional probabilities are assumed to be Gaussian distributed with four parameters $(\mu_i^1, \sigma_i^1, \mu_i^0, \sigma_i^0)$

$$p(v_i|y=1) = \mathcal{N}(\mu_i^1, \sigma_i^1), \quad p(v_i|y=0) = \mathcal{N}(\mu_i^0, \sigma_i^0)$$

Online Learning Model

Update rules for parameters

$$\sigma_i^j \leftarrow \sqrt{\lambda\left(\sigma_i^j\right)^2 + (1-\lambda)\left(\tilde{\sigma}_i^j\right)^2 + \lambda(1-\lambda)\left(\mu_i^j - \tilde{\mu}_i^j\right)^2}$$

$$\mu_i^j \leftarrow \lambda\mu_i^j + (1-\lambda)\tilde{\mu}_i^j$$

$$(i = 1,2,\dots,n;\ j = 0,1)$$

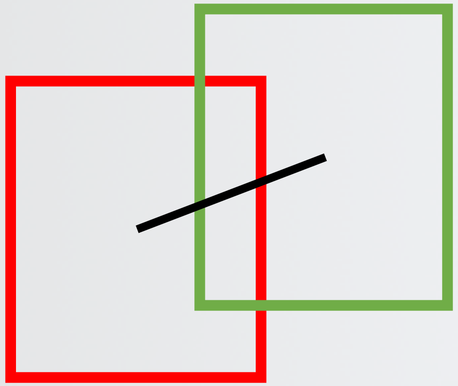
where $\lambda \in (0,1)$ is the inertial factor that controls the updating speed and

$$\tilde{\mu}_i^j = \frac{1}{|S_j|}\sum_{k\in S_j} v_i(k)$$

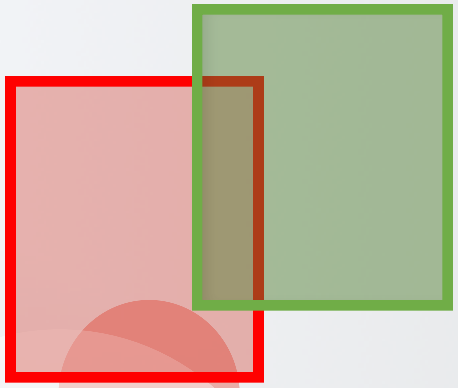
$$\tilde{\sigma}_i^j = \sqrt{\frac{1}{|S_j|}\sum_{k\in S_j}\left(v_i(k) - \tilde{\mu}_i^j\right)^2}$$

Evaluation Methodology

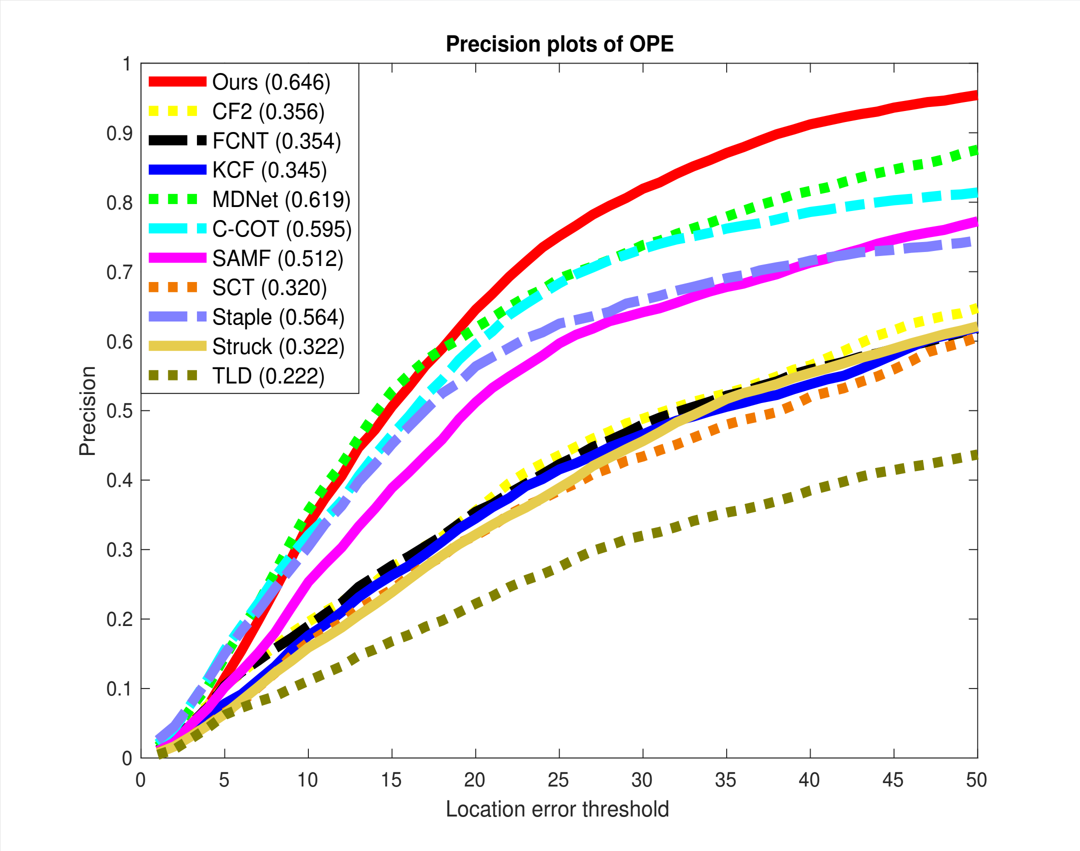
Center Location Error (CLE)



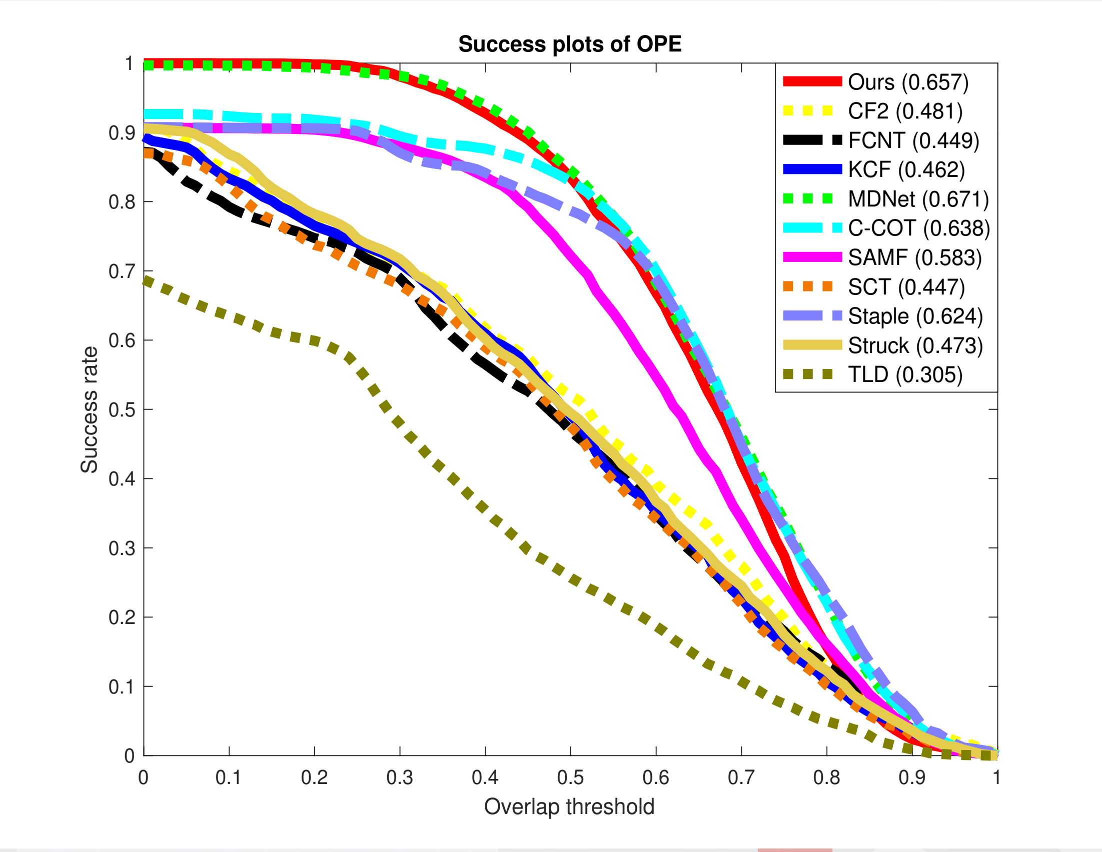
Pascal VOC overlap ratio (VOR)



Experimental Results

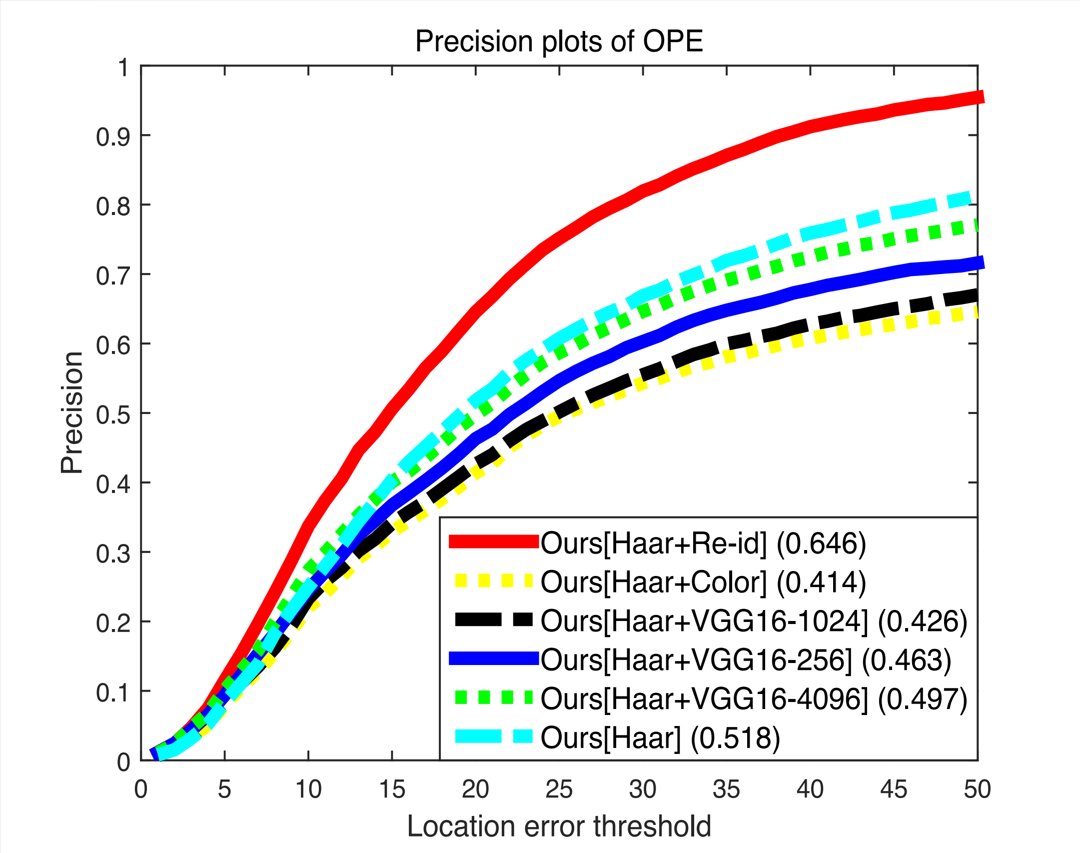


Precision Curve

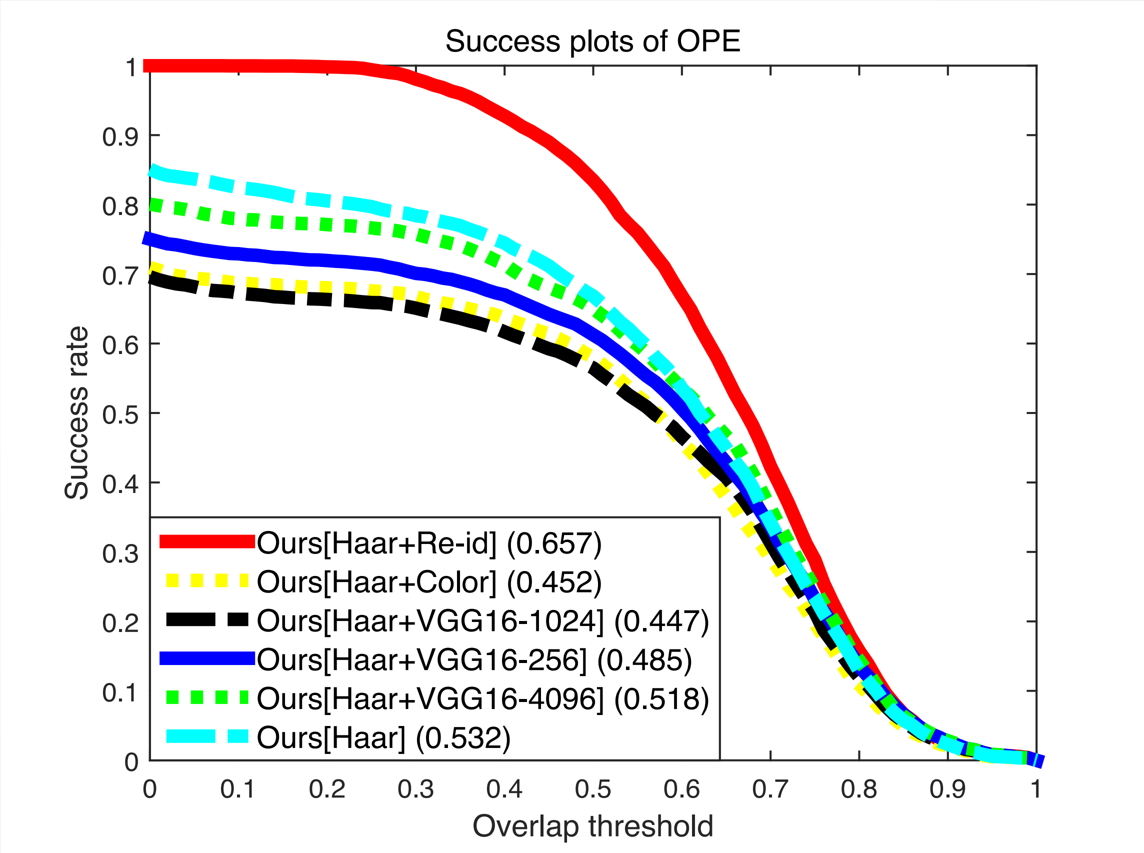


Success Curve

Effectiveness of Deep Re-id Feature



Precision Curve



Success Curve

Video Demo

https://www.youtube.com/watch?v=HQIi0Z9b4Pw

Thank you!