Online Graph-Based Tracking

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Problem

- ***Motivation:*** Visual tracking relying on a chain model is not reliable in challenging situations.
- ***Objective:*** Online tracking which adaptively constructs a graph structure based on the target characteristic.
- ***Our approach:*** Track the current frame using multiple previous frames selected by representability and weighted by tracking suitability.

Main Framework

1 Density Propagation

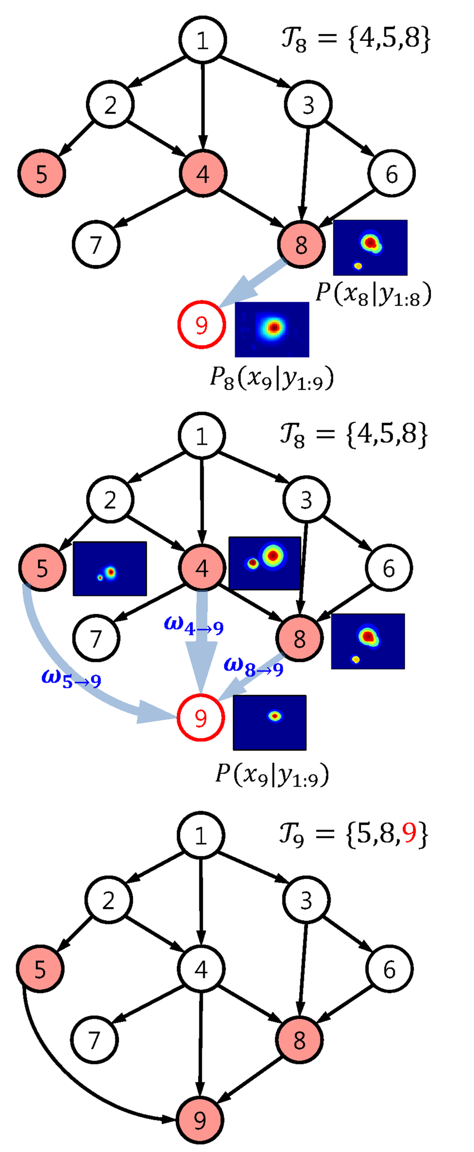
- Propagate density functions from representative frames through a patch matching.

2 Density Aggregation

- Estimate the target posterior by a weighted Bayesian model averaging, where the weights are computed by tracking plausibility.

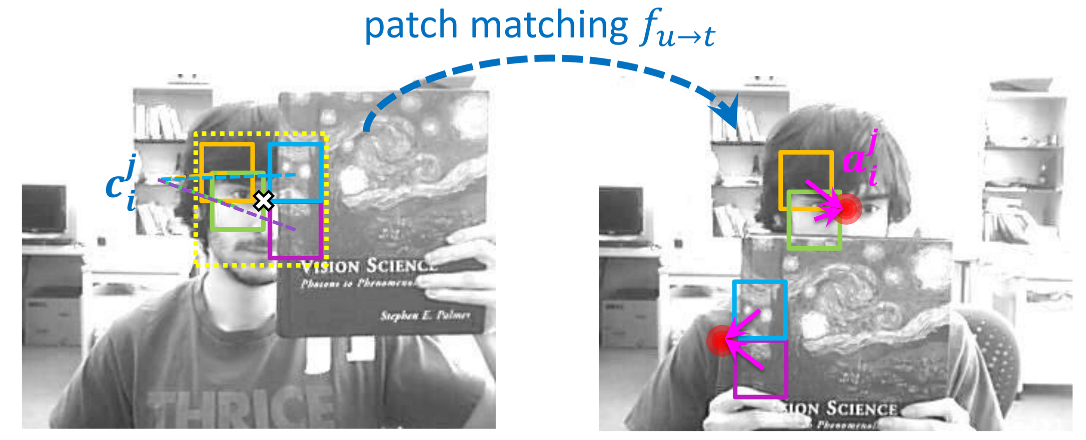
3 Model Update

- Evaluate the reliability of the tracking result and update the representative frame set if necessary.



1 Density Propagation

- Propagate a posterior by patch matching and voting procedure [1].
  - Prediction and update steps are jointly implemented by patch matching and center voting.



$$P_u(\mathrm{x}_t|\mathrm{y}_{1:t}) = \alpha_{u\to t} P_u(\mathrm{y}_t|\mathrm{x}_t) \int P(\mathrm{x}_t|\mathrm{x}_u) P(\mathrm{x}_u|\mathrm{y}_{1:u}) d\mathrm{x}_u$$

$$\approx \sum_{\mathrm{x}_u^i \in \mathbb{S}_u} \sum_{j=1}^{r_u^i} \mathcal{N}(\mathrm{x}_t; f_{u\to t}(c_i^j) - a_i^j, \Sigma)$$

$\mathbb{S}_u$: A set of samples drawn from $P_u(\mathrm{x}_u|\mathrm{y}_{1:u})$

[1] Hong, S., Kwak, S., Han, B.: Orderless tracking through model-averaged posterior estimation. In: ICCV. (2013)

2 Density Aggregation

- Weighted Bayesian Model Averaging.

$$P(\mathrm{x}_t|\mathrm{y}_{1:t}) \propto \sum_{u\in\mathcal{T}_{t-1}} \omega_{u\to t} P_u(\mathrm{x}_t|\mathrm{y}_{1:t})$$

$\mathcal{T}_{t-1}$: A set of representative frames when tracking t

- The weight is determined by potential tracking error.

$$\omega_{u\to t} = \frac{\exp(-\eta\cdot\delta_{u\to t})}{\sum_{s\in\mathcal{T}_{t-1}}\exp(-\eta\cdot\delta_{s\to t})}$$

$\delta_{u\to t}$: The potential error of tracking $u\to t$

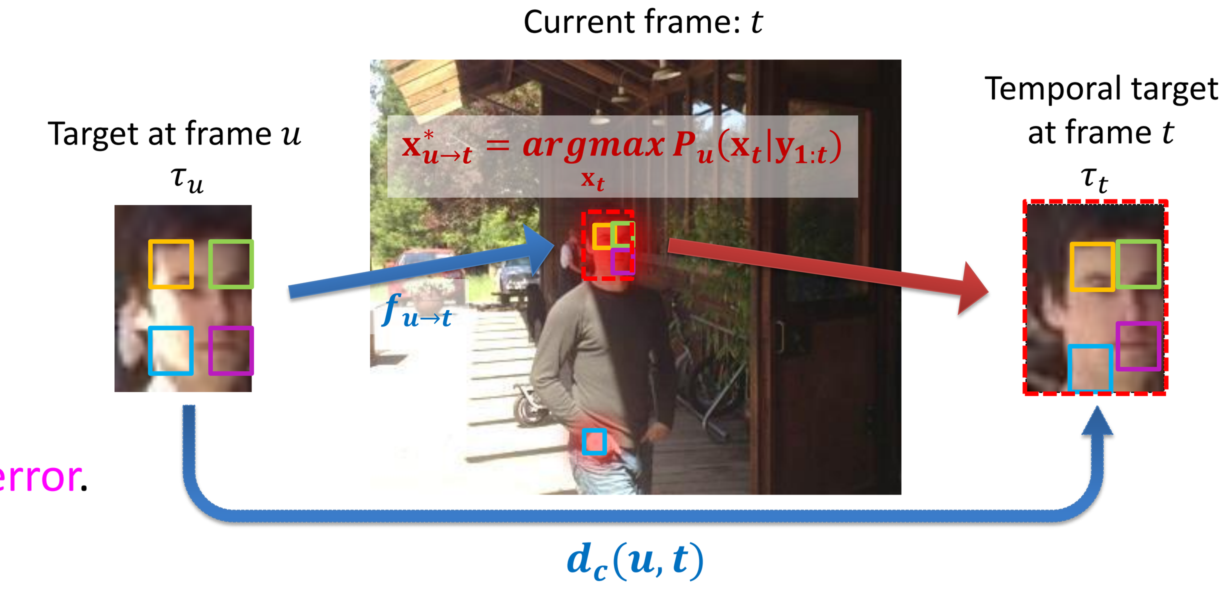
$$\delta_{u\to t} = \max(d_c(u,t), \delta_u)$$

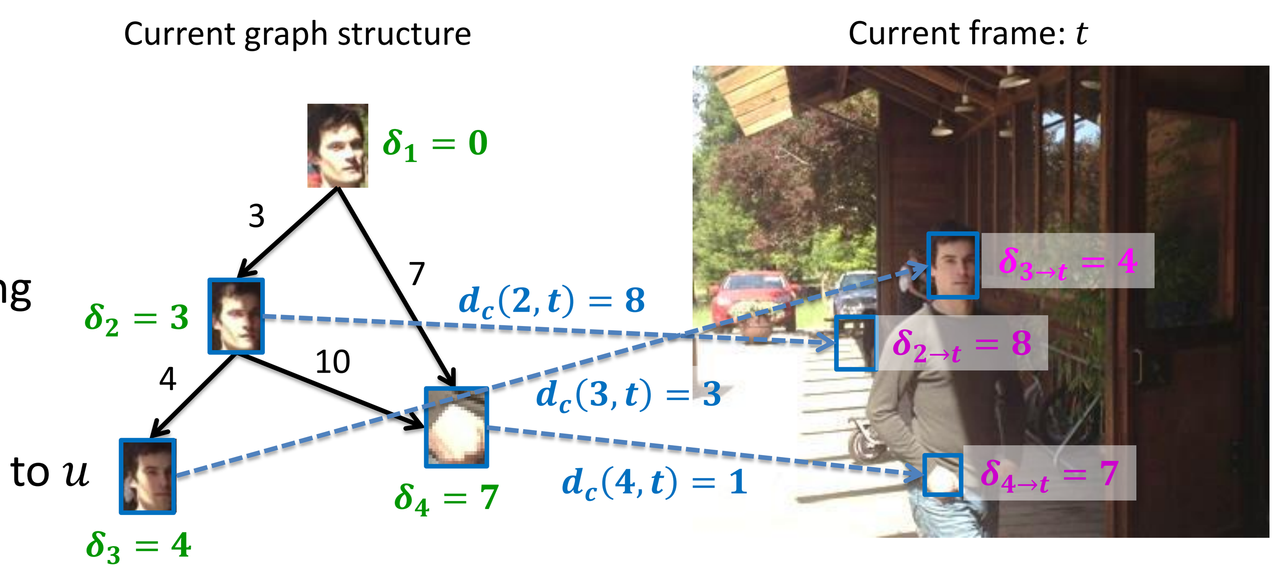
$d_c(u,t)$: The deformation cost by patch matching

$$d_c(u,t) = \operatorname{median}_j \| c_u^j - f_{u\to t}(c_u^j;\tau_t)\|$$

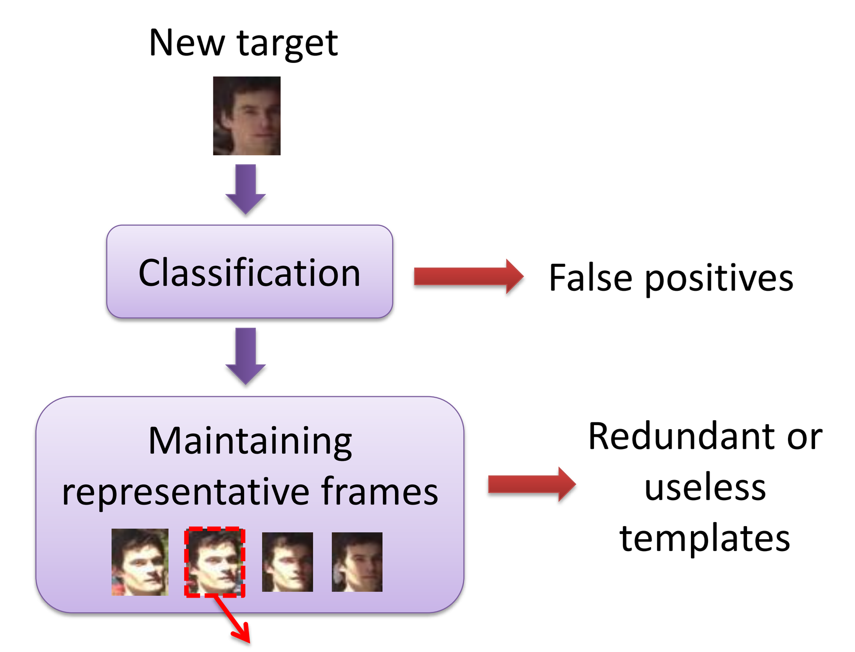
δ_u: The *minimax* distance from the initial frame to u

$$\delta_u = \min_{v\in\mathcal{T}_{u-1}} \delta_{v\to u} = \min_{v\in\mathcal{T}_{u-1}} \max(d_c(v,u), \delta_v)$$





3 Model Update



Classification

- Prevent false tracking results from entering the representative frame set.
  - A set of positive and negative templates

$$\mathcal{D}_{t-1} = \{\tau_1^+, \ldots, \tau_{N_p}^+, \tau_1^-, \ldots, \tau_{N_n}^-\}$$

  - New target template τ_t^* is positive if

$$\frac{S_p}{S_p + S_n} < \rho$$

S_p: The average Euclidean distance between τ_t^* and k-nearest positive templates in D_{t-1}

S_n: The Euclidean distance between τ_t^* and the nearest negative template in D_{t-1}

Maintaining representative frames

- Each template in the representative frame set should be distinct and useful for the further tracking.

Distinctiveness

$$\kappa_u^{(1)} = \min_{v\in\mathcal{T}_{t-1}\setminus\{u\}} \Delta(u,v)$$

patch matching distance

Usefulness

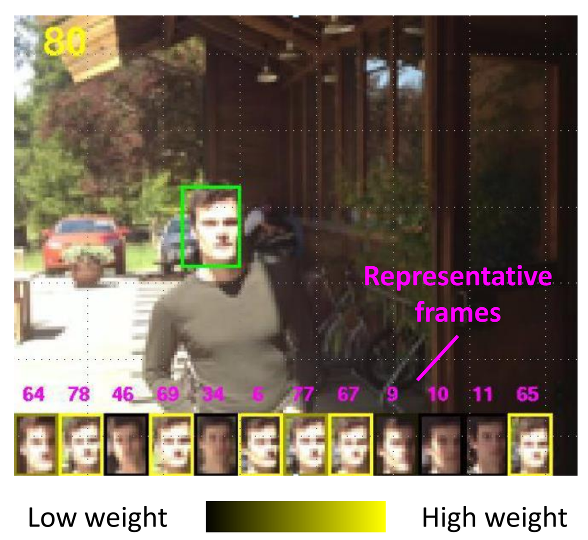
$$\kappa_{u,t}^{(2)} = (1 + \sigma y_t \omega_{u\to t})\kappa_{u,t-1}^{(2)}$$

classification result (+1 or -1)

$$\kappa_{u,t} = \kappa_u^{(1)} \cdot \kappa_{u,t}^{(2)}$$

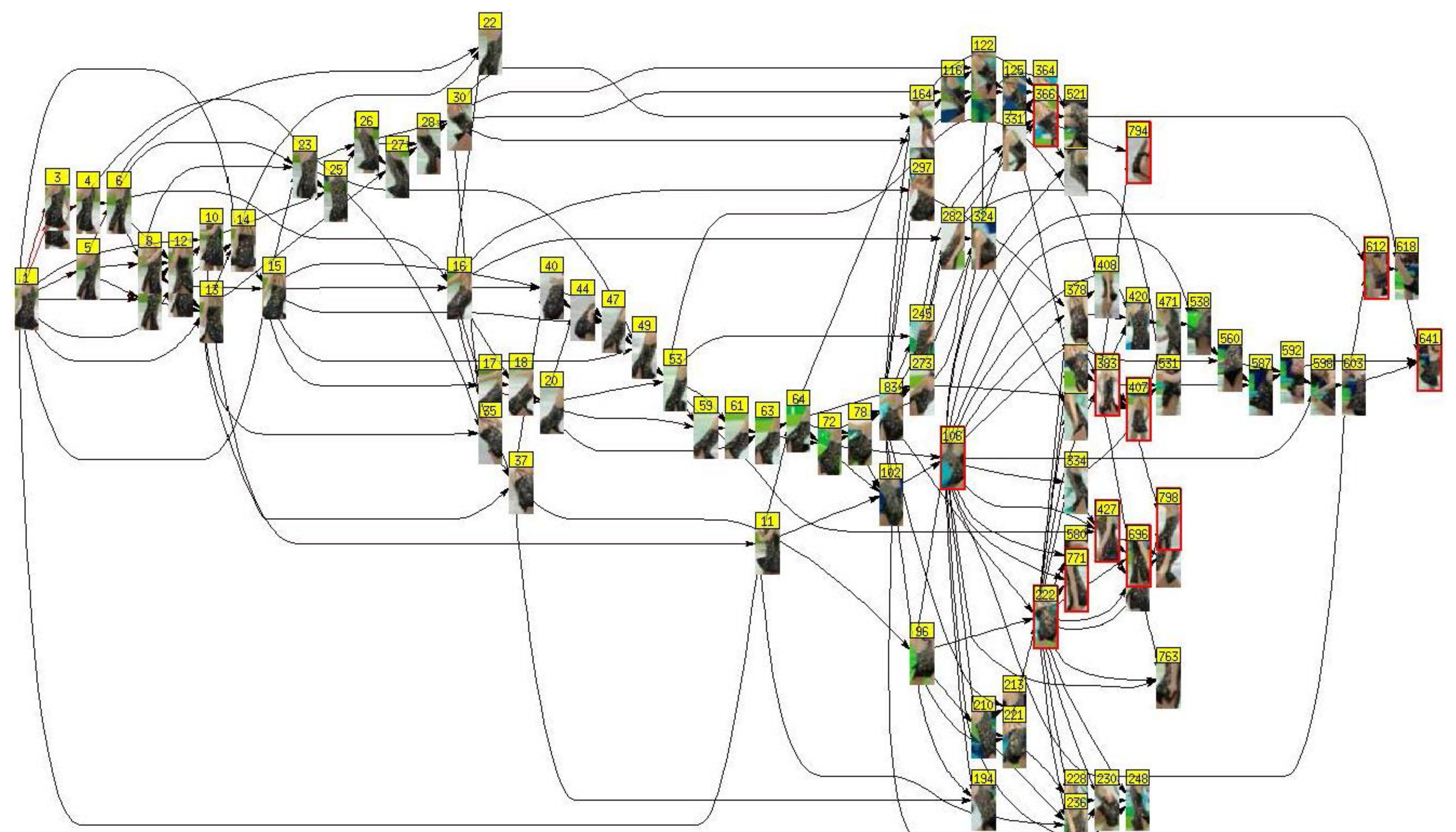
$$m = \operatorname{argmin}_{u\in\mathcal{T}_{t-1}} \kappa_{u,t}$$

$$\mathcal{T}_t = \begin{cases} (\mathcal{T}_{t-1} \setminus \{m\}) \cup \{t\} & \text{if } \kappa_{t,t} > \kappa_{m,t} \\ \mathcal{T}_{t-1} & \text{otherwise} \end{cases}$$



Experiments

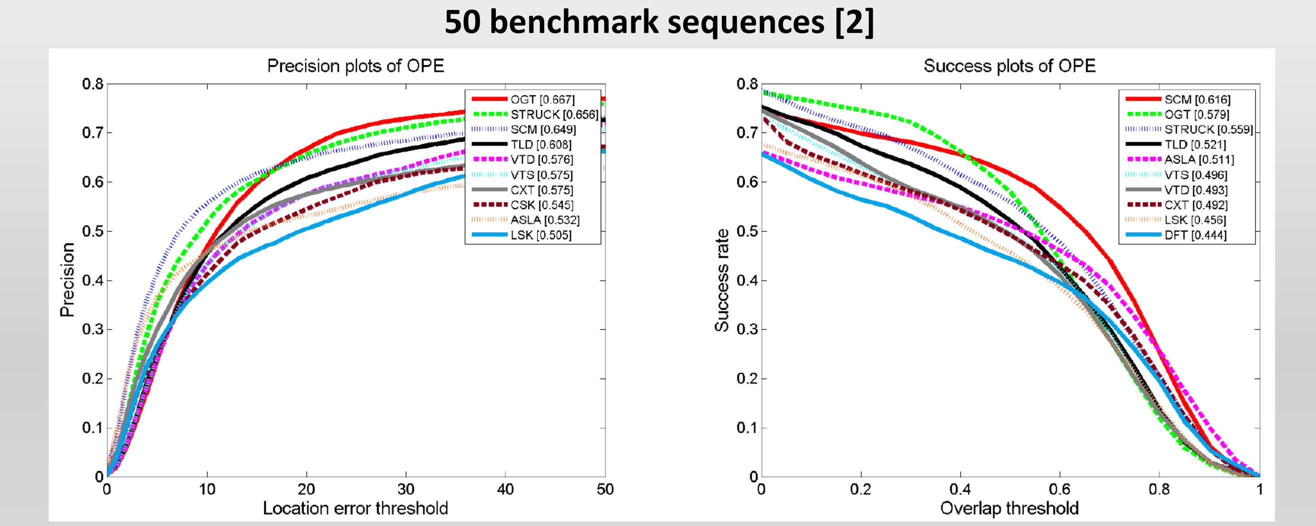
- **Identified graph structure (*skating* sequence)**



- **Quantitative results**

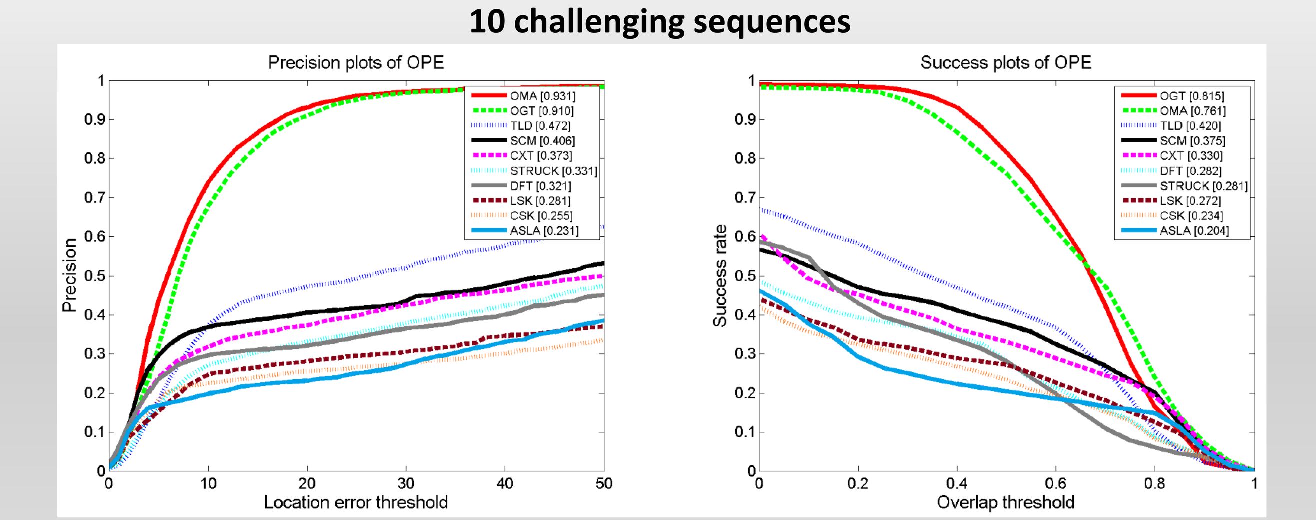
Our tracker: OGT (Online Graph-based Tracker)

50 benchmark sequences [2]



[2] Wu, Y., Lim, J., Yang, M.H.: Online object tracking: A benchmark. In: CVPR. (2013)

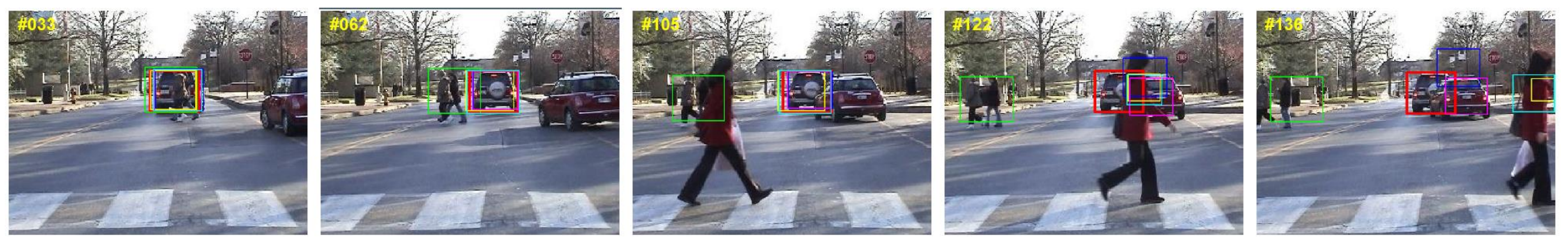
10 challenging sequences



- **Qualitative results**

OGT — CXT — SCM — ASLA — TLD — STRUCK

Abrupt motion (*bike* sequence)



Occlusion (*campus* sequence)

Shot change (*psy* sequence)