Detection- and Trajectory-Level Exclusion in Multiple Object Tracking

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Motivation and Overview

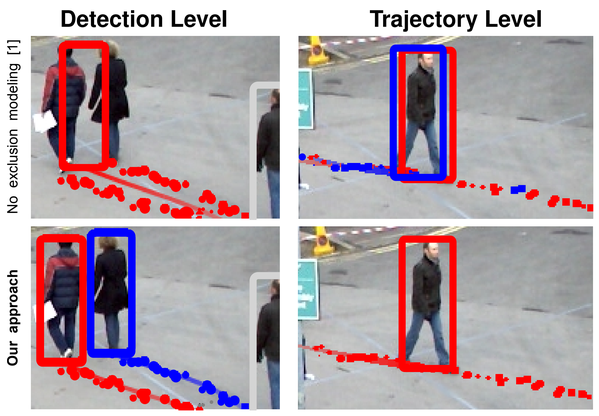
Accurate multi-target tracking requires that

- two simultaneous detections cannot be caused by the same target, and
- two trajectories have no spatio-temporal overlap.

Dealing with both requirements is challenging.

Previous work handled exclusion either only at the detection level, *e.g.*, [3] or only at the trajectory level, *e.g.*, [2].

We introduce *simultaneous exclusion handling* for both:



Our Contributions

- Exclusion modeling at detection level
- Exclusion modeling at trajectory level
- Novel co-occurrence label cost
- α-expansion-based energy minimization algorithm
- Statistics-based design of energy components

Discrete-Continuous Energy with Exclusion

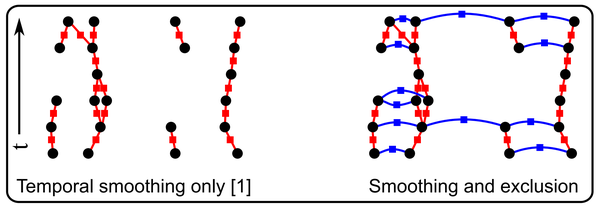
Discrete-continuous formulation (*cf.* [1]):

$$E(\mathbf{f}, \mathcal{T}) = \underbrace{\sum \phi(\mathsf{f_d}, \mathcal{T})}_{\text{data}} + \underbrace{\sum \psi_{\mathsf{S}}(\mathsf{f_d}, \mathsf{f_{d'}})}_{\text{temp. smoothness}} + \underbrace{\sum \psi_{\mathsf{X}}(\mathsf{f_d}, \mathsf{f_{d'}})}_{\text{det.-level excl.}} + \underbrace{\sum h_{\mathbf{f}}(\mathcal{T}_i)}_{\text{label cost (per-trajectory cost)}} + \underbrace{\sum h^{\mathsf{X}}_{\mathbf{f}}(\mathcal{T}_i, \mathcal{T}_j)}_{\text{pairwise label cost (trajectory co-occurrence cost)}}$$

Labeling
Trajectories

Detection-Level Exclusion

Goal: Enforce unique IDs for all detections in one frame.



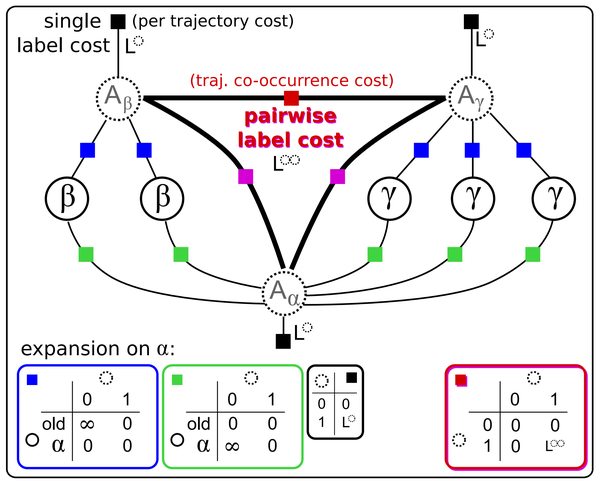
Apply cost $\psi_{\mathsf{X}}(\mathsf{f_d}, \mathsf{f_{d'}}) = \begin{cases} \overline{\psi}_{\mathsf{X}}, & \mathsf{f_d} = \mathsf{f_{d'}} \\ 0, & \text{otherwise} \end{cases}$

to all edges between simultaneous detector responses

$$(\mathsf{d}, \mathsf{d}') \in \mathbf{E}_{\mathcal{X}} = \left\{ \left(\mathsf{d}^{\mathsf{t}}_{\mathsf{i}}, \mathsf{d}^{\mathsf{t}}_{\mathsf{j}}\right) \middle| \mathsf{i} \neq \mathsf{j}, \underbrace{\left\|\mathbf{D}^{\mathsf{t}}_{\mathsf{i}} - \mathbf{D}^{\mathsf{t}}_{\mathsf{j}}\right\| > s/2}_{\text{allow for occasional double detection}} \right\}.$$

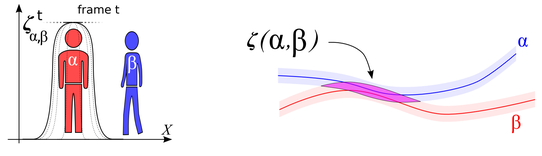
Trajectory-Level Exclusion

Goal: Suppress solutions with incompatible trajectories.



A co-occurrence term penalizes a labeling $\mathbf{f}$ with overlapping trajectories:

$$h^{\mathsf{X}}_{\mathbf{f}}(\alpha, \beta) = \begin{cases} \zeta(\alpha, \beta), & \exists \mathsf{d}, \mathsf{d}' : \mathsf{f_d} = \alpha \wedge \mathsf{f_{d'}} = \beta \\ 0, & \text{otherwise.} \end{cases}$$



Optimization

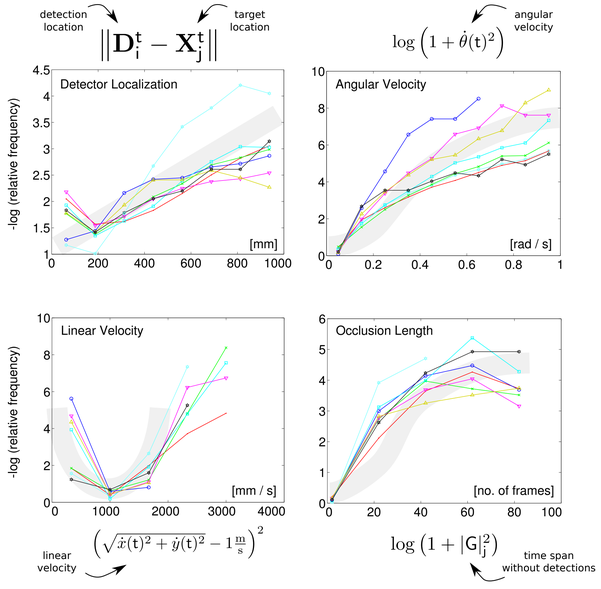
- Discrete part has non-submodular, global terms.
- Continuous part is non-convex.

Alternate between both energy parts:

Discrete	**Continuous**
α-expansion augmented with greedy label removal.	Gradient-based optimization.

Statistical Analysis

Goal: Derive functional form of energy from real data.



References

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[2] A. Milan, S. Roth, and K. Schindler. Continuous energy minimization for multi-target tracking. *PAMI*. To appear.

[3] B. Yang and R. Nevatia. An online learned CRF model for multi-target tracking. In *CVPR 2012*.

[4] H. Pirsiavash, D. Ramanan, and C. Fowlkes. Globally-optimal greedy algorithms for tracking a variable number of objects. In *CVPR 2011*.

[5] C.-H. Kuo and R. Nevatia. How does person identity recognition help multi-person tracking? In *CVPR 2011*.

Experiments

- Public, challenging datasets: PETS'09, TUD and ETH.
- Publicly available ground truth, detections and evaluation script [1, 3].

Qualitative results

Quantitative evaluation

LOO cross-validation results on six sequences

Method	MOTA	MOTP	MT	ML	FM	ID
DP [4]	37.4%	64.8%	7	17	104	114
DCO [1]	42.2%	64.1%	11	12	48	65
statistics	45.4%	60.8%	11	12	41	55
det. exclusion	46.7%	63.0%	11	12	38	48
traj. exclusion	46.6%	62.7%	10	12	49	69
combined	51.5%	64.4%	11	13	43	54

Comparison to other methods

Method	Recall	Prcsn	MT	ML	FM	ID
DP [4]	67.4%	91.4%	50.2%	9.9%	143	4
PIRMPT [5]	76.8%	86.6%	58.4%	8.0%	23	11
Online CRF [3]	79.0%	90.4%	68.0%	7.2%	19	11
Our method*	77.3%	87.2%	66.4%	8.2%	69	57

*Augmented with a simple tracklet linking scheme.

Summary

We incorporated exclusion modeling into a discrete-continuous CRF

- at the detection level using non-submodular constraints,
- at the trajectory level using a co-occurrence label cost.

Moreover, we proposed an expansion move-based optimization scheme and presented a strategy to derive individual energy components from a statistical analysis of ground-truth annotations.

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visual inference /visinf @visinf