From Certain to Uncertain: Toward Optimal Solution for Offline Multiple Object Tracking

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Offline multiple object tracking

same or different objects? $\longrightarrow$ affinity measure

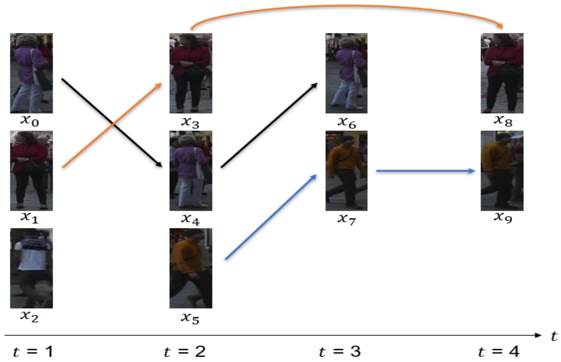


Figure 1: An example of object tracking. The task is to assign identities for detected objects across a series of frames.

Uncertain region and early mistakes

1. imperfect affinity measure $\longrightarrow$ uncertain region $\longrightarrow$ threshold θ $\longrightarrow$ mistakes
2. sequential tracking with pre-decided θ $\longrightarrow$ early mistakes

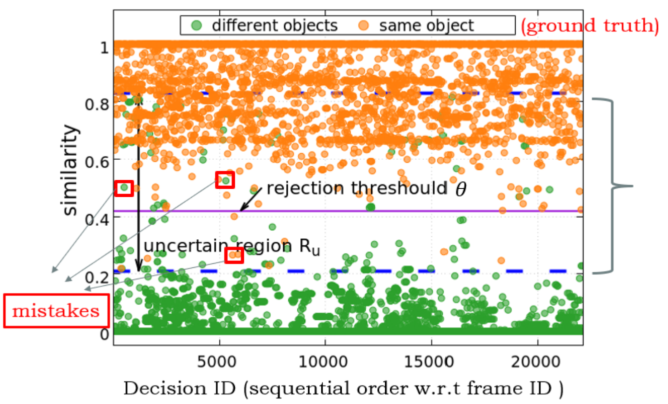
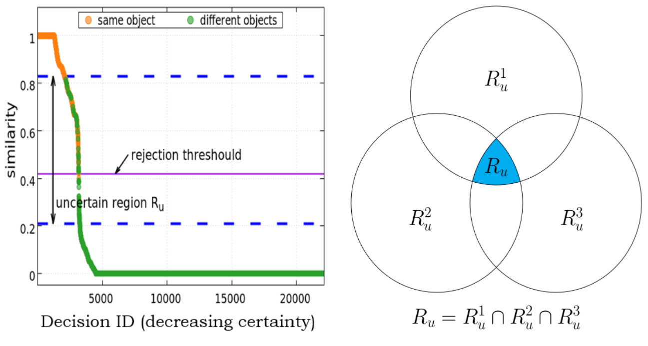


Figure 2: Two typical issues for previous offline object tracking.

Ideas to tackle the two issues



(a) tracking from certain to uncertain (b) ensemble multiple tracking experts

Figure 3: Ideas to tackle uncertain region and early mistake issues.

Our proposal

Agglomerative Hierarchical Clustering with Ensemble of Tracking Experts (AHC_ETE)

Notations

S: image sequence; D: detection set; N: number of detections; x_i: i^{th} detection; T_k: k^{th} track; e: a tracking expert (method)

Adapting AHC for object tracking

- memory complexity: $\mathcal{O}(N^2) \longrightarrow$ dividing S into $S_1, ..., S_n$, reduced to $\mathcal{O}(N_i^2)$;
- spatio-temporal constraint: detections in the same image should not belong to the same track $\longrightarrow$ building **cannot-link constraints**

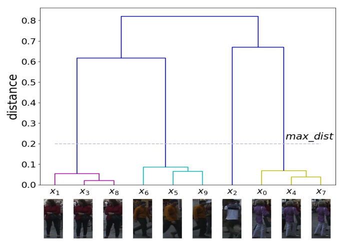


Figure 4: AHC based tracking

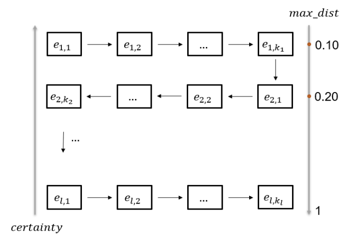


Figure 5: AHC_ETE framework

Defined distance measures

Appearance distance

$$\mathbf{dist}_{appe}(x_i, x_j) = 1 - \frac{a_i^T a_j}{||a_i||\ ||a_j||} \qquad (1)$$

a_i: extracted CNN feature vector of x_i

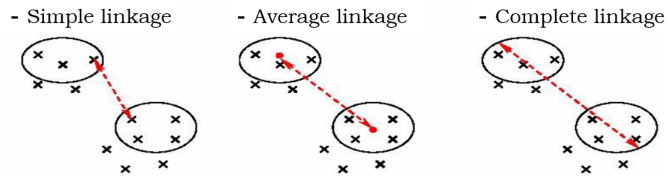


Figure 6: Linkages for the distance between two clusters

Motion (Kalman Filter) distance

state of object: $(u, v, \gamma, h, \dot{u}, \dot{v}, \dot{\gamma}, \dot{h})$ [Wojke et al., 17], centers, aspect ratio, height of a bbox

$$\mathbf{dist}_{kf}^{'}(T, x) = \sqrt{(y - \hat{y})^T \mathbf{\Sigma}^{-1} (y - \hat{y})} \qquad (2)$$

y: detection, $\hat{y}$: prediction of Kalman Filter

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Temporal distance

Γ_k: set of frame IDs for detections in T_k

$$dist_{temp}(T_u, T_v) = \begin{cases} |\Gamma_u \cap \Gamma_v| - |\Gamma_u \cup \Gamma_v| & \text{if } \Gamma_u \cap \Gamma_v \neq \emptyset \\ min(\Gamma_v) - max(\Gamma_u) & \text{elseif } max(\Gamma_u) < min(\Gamma_v) \\ min(\Gamma_u) - max(\Gamma_v) & \text{elseif } max(\Gamma_v) < min(\Gamma_u) \\ 0 & \text{else} \end{cases} \quad (4)$$

frame IDs overlap $\rightarrow$ negative value; one track appears later than another $\rightarrow$ closest frame gap; no overlap & not earlier, later tracks $\rightarrow$ 0

Integrated distance

$$\text{dist}(T_u, T_v) = dist_{major}(T_u, T_v) * F_1(\cdot) * F_2(\cdot) * \ldots \quad (5)$$

We use appearance distance $dist_{appe}$ as $dist_{major}$, $F(\cdot)$ to filter other distances.

$$F(\nu, condition) = \begin{cases} 1 & \text{if } \nu \text{ satisfies } condition, \\ inf & \text{else.} \end{cases} \quad (6)$$

Defined tracking experts

1. Preprocessing: build T_{fp} for detections with $score \leq 0.3$ or suppressed by NMS with threshold 0.1; impose cannot-links for T_{fp}, i.e., for any track T_k, $dist(T_k, T_{fp}) = inf$.
2. Connecting detections to tracks: track with *complete* linkage (e_1), then *single* linkages (e_2 and e_3) $\rightarrow$ remove cannot-links on T_{fp} and track with weak constraints (e_4 and e_5)
3. Post-processing: remove T_k if $|T_k| < 3$

Table 1: Settings of our defined experts. Here ***appe***, ***temp*** and ***kf*** represent the settings for the appearance, temporal and Kalman Filter distance, respectively.

E	$dist_{appe}$	$F_1(temp)$	$F_2(kf)$	$F_3(appe)$	max_dist
e_1	complete	≥ 0	complete: < 9.5	-	0.10
e_2	single	≥ 0	-	-	0.05
e_3	single	≥ 0	complete: < 9.5	-	0.10
e_4	single	≥ 0	complete: < 9.5	-	0.10
e_5	single	≥ 0	average: < 9.5	complete: ≤ 0.30	0.20

Design of experiments

Dataset: MOT15, MOT16 [Milan et al., 16] training sequences

Evaluation metrics: multiple object tracking accuracy (MOTA [Bernardin and Stiefelhagen, 08]), identification precision (IDP), recall (IDR), corresponding F_1 score (IDF$_1$ [Ristani et al., 16])

Benchmark: Deep Sort [Wojke et al., 17] (same features, appearance and motion distances)

Result: effects of merging order

our method generally outperforms Deep Sort [Wojke et al., 17]; IDF$_1$s, IDPs, IDRs and MOTAs generally increase as more experts integrated

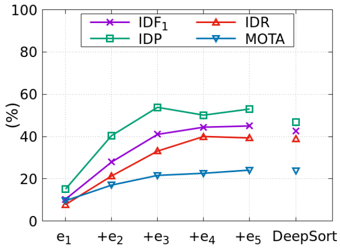

Figure 1: MOT15

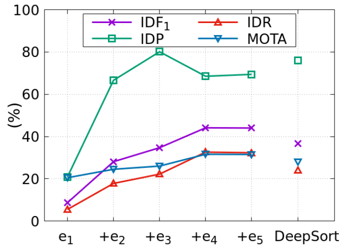

Figure 2: MOT16

Result: effects of different linkages

standard AHC [Day and Edelsbrunner, 84] based tracking

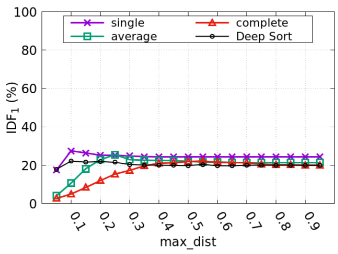

Figure 3: IDF1

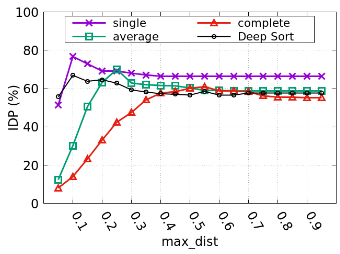

Figure 4: IDP

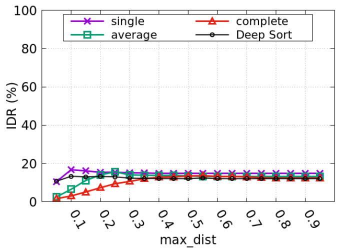

Figure 5: IDR

Test data: MOT16-02

best IDF$_1$s, IDPs and IDRs differ; certain region of *single* $<$ *average* $<$ *complete* linkage

Conclusion

- Tackling two typical issues for object tracking: 1) uncertain region, 2) early mistakes
- Proposed AHC_ETE: tracking from certain to uncertain, ensemble multiple tracking experts (a general framework for various distance measures and tracking experts)

Limitations and future work

- accepted all the progress of earlier experts $\rightarrow$ sensitive to the ordering of experts
- further experiments comparing with the state-of-the-art methods needed

Acknowledgments

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Code: https://github.com/cyoukaikai/ahc_ete