REDUCING FALSE POSITIVES IN OBJECT TRACKING WITH SIAMESE NETWORK

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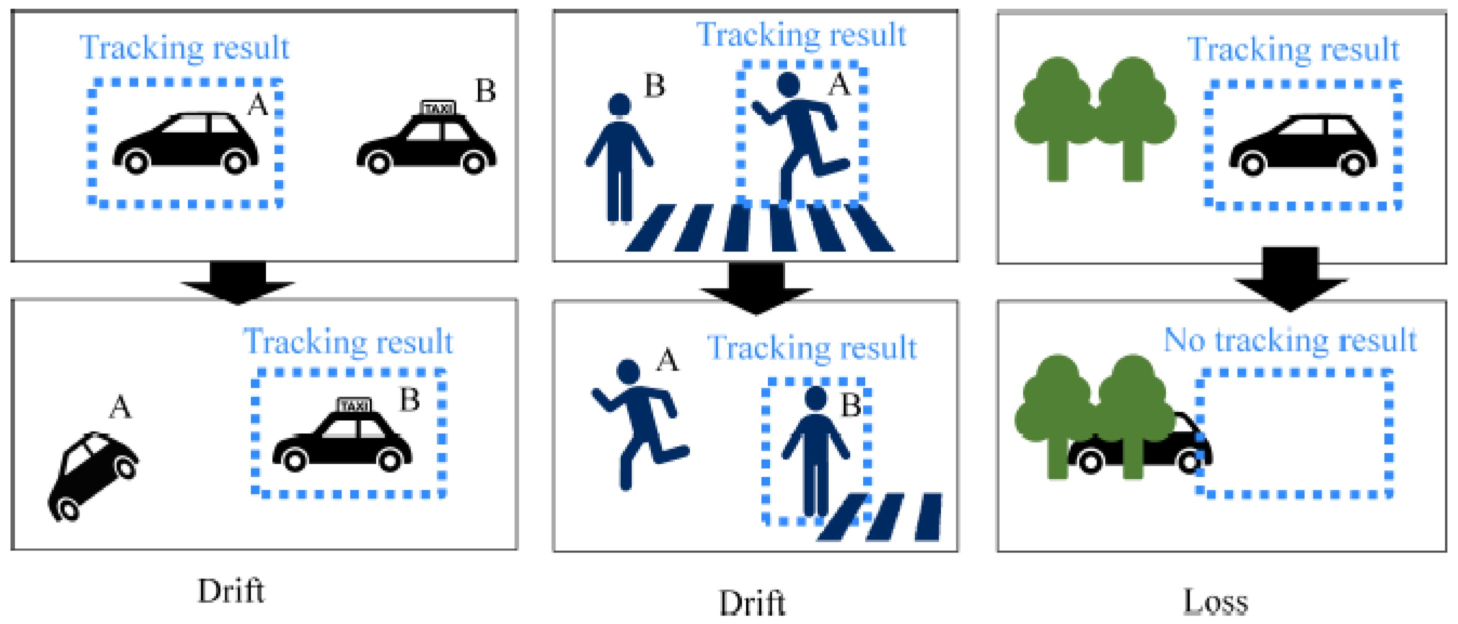
Introduction: Single object tracking

Background: Practical long-term tracking is needed for real-time surveillance

Problems: Drift and loss of the target

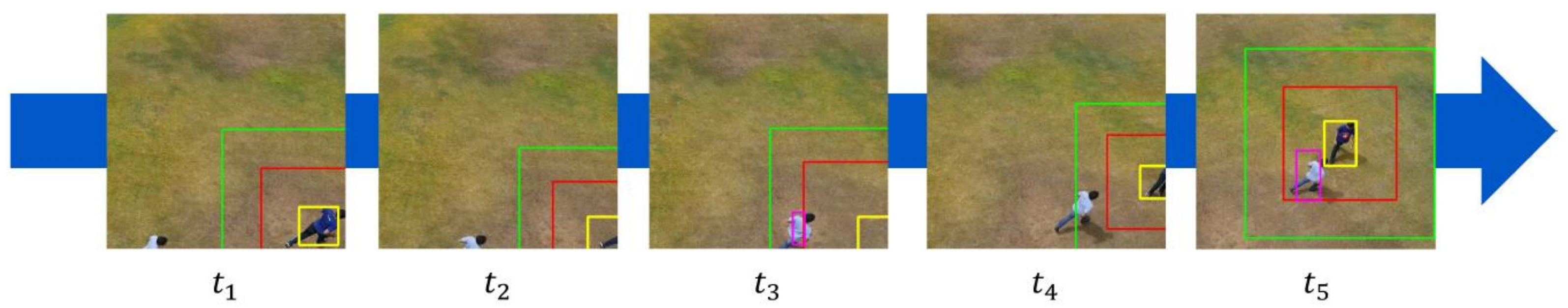


Goal: Reduce the occurrence of drift and recover from the loss of the target

Concept of our method

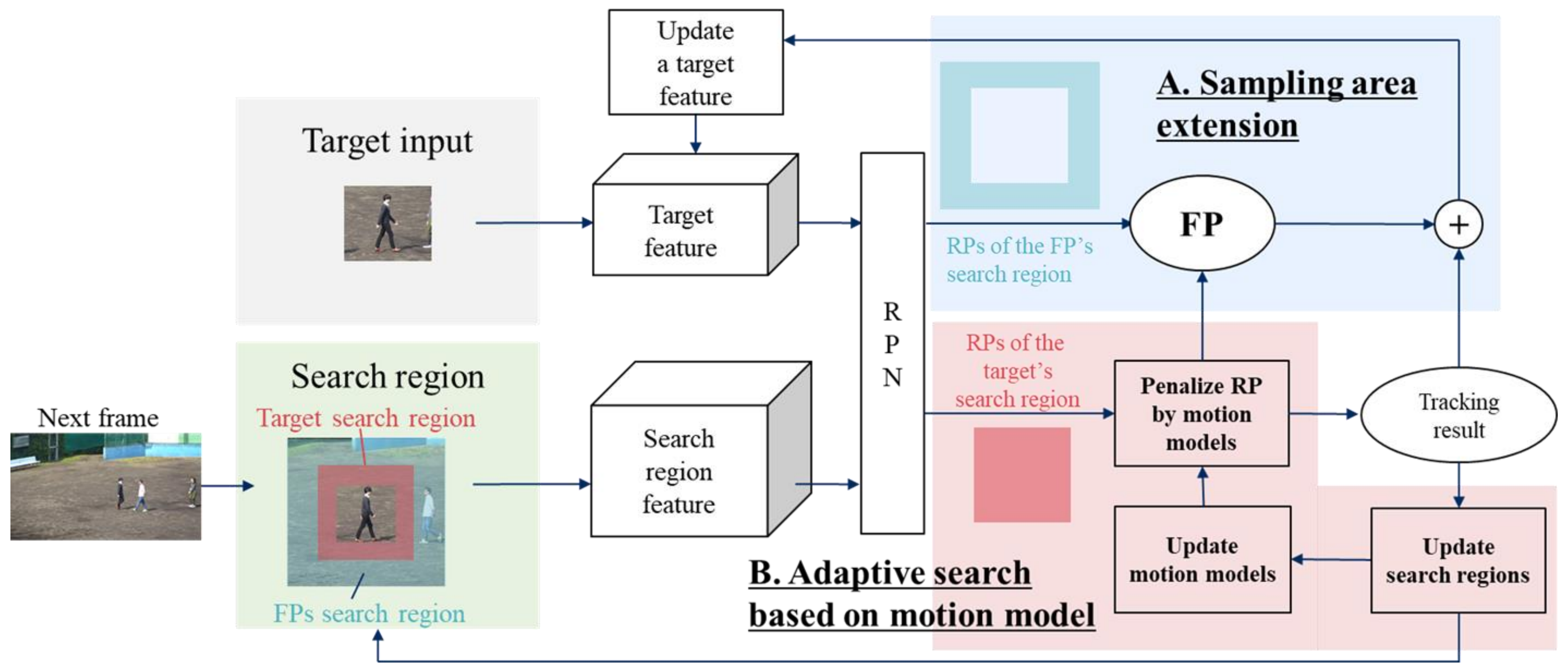
Conventional [1] : Drift to similar object and never re-track the target

Proposed : Recognize the similar objects in advance and keep tracking a true target



Proposed frameworks

2 frameworks for avoiding drift/loss of the target



FPC = false positive candidate, RP=region proposal

A. Sampling area extension

Online learning of similar objects before approaching

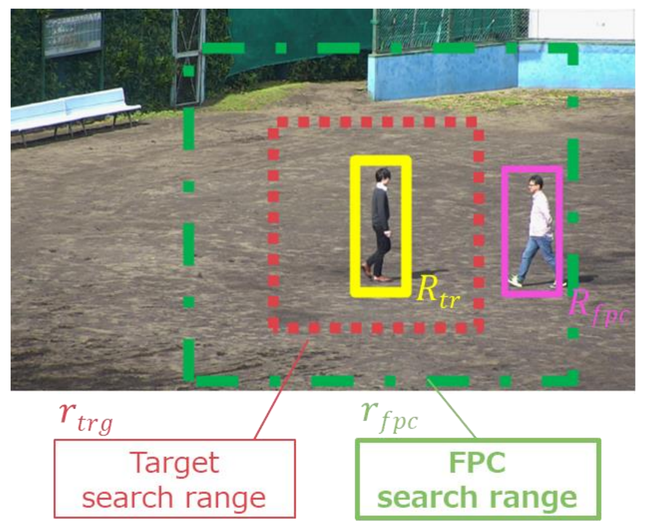
- Extend a sampling area for the false positive candidates only
  - Similar object = false positive candidate (FPC)
  - Able to recognize and learn FPC in advance
- Conditions for sampling FPC
  - Reliability L_{fpc} near the boundary

$$0.5 \le Lf_{pc} \le 0.9$$

  - Low IoU with the target

$$IoU(R_{tr}, Rf_{pc}) < 0.1$$

- Online learning
  - Same as conventional method [1]
    – Embedded feature difference between the target and FPCs



$$T_{base} = \sqrt{w^2 + h^2}$$
$$r_{trg} = k * Tbase$$
$$r_{fpc} = b * Tbase$$
$$1 \le k < b$$

B. Adaptive search based on motion models

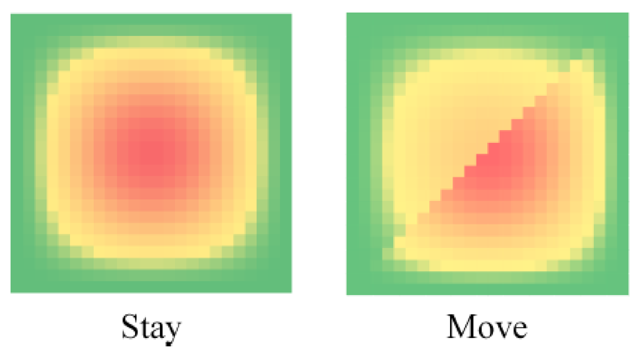
Weighting inside a search region by its motion to reduce drifting

- Adopt motion models (Stay/Move)
  - Adjust a position reliability W by its motion

$$W = w_{2D} * R(\theta) * \begin{pmatrix} 1 & 1 & 1 \\ 1 & c & d \\ 1 & d & d \end{pmatrix}$$

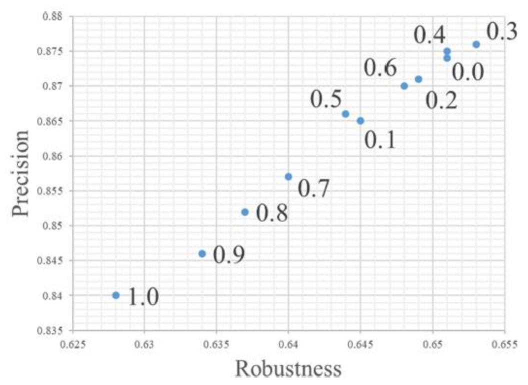
$R(\theta)$: Rotation Matrix, w_{2D}: 2D cosine window

$$c = \begin{cases} 1 + \beta & (stay) \\ 1 & (move) \end{cases} \qquad d = \begin{cases} 1 & (stay) \\ \gamma & (move) \end{cases}$$



  - Determine motion constraint value β, γ by experiment

$$\beta = 1.0, \quad \gamma = 0.3$$



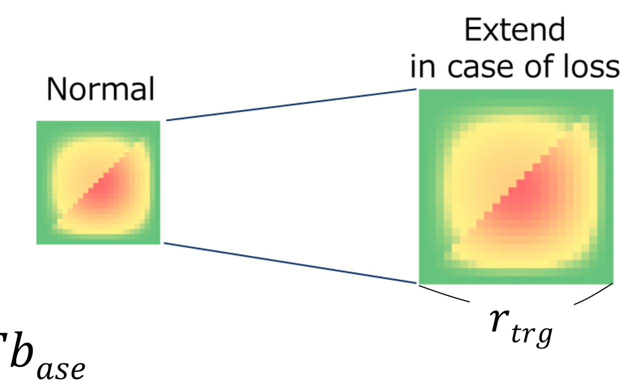
Extend the search region in case of losing the target

- Detect loss by target reliability L_{trg}

$$L_{trg} \le 0.6$$

- Extend the search region according to the num. of consecutive loss

$$r_{trg} = (k + \tau * nl_{oss} * a) * Tb_{ase}$$



τ : an adjusting parameter of the expansion amount
n_{loss} : the frame number of the latest consecutive loss
a : a target acceleration just before loss

Experiments

I. Ablation Study

- Metric
  - Long-term tracking benchmark dataset: UAV123[2]
    – Long-term tracking dataset includes absence of the target (causes drift and loss)
  - One-pass evaluation (OPE)

A	B	Robustness	Precision
–	–	0.489	0.725
✓	–	0.570	0.776
–	✓	0.564	0.758
✓	✓	**0.595**	**0.791**

- Score improvement
  - Combining proposed 2 framework: **Improved 21.7% for robustness**
- Speed improvement
  - **3 times faster (95.7 FPS)** than a video capture speed (30 FPS)

Method	SiamRPN [5]	DaSiamRPN [1]	gSiam (Proposed)
FPS	**169.6**	29.1	95.7

Both frameworks improved robustness and the combination is better

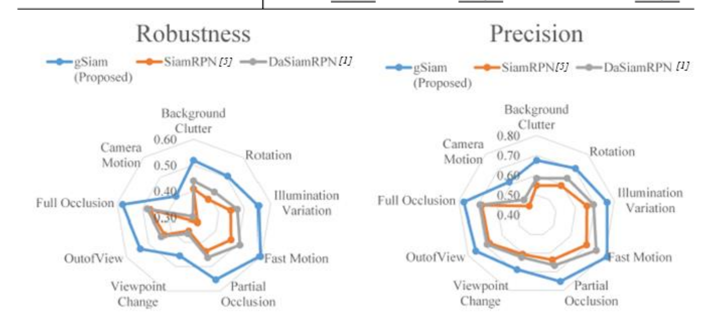
II. Comparison with exiting methods

- Dataset variation
  - 3 long-term tracking benchmarks

Dataset	UAV123[2]	LaSOT [3]	VOT2018-LT[4]
No. of seq.	123	280	35
No. of classes	9	70	11
Min len. of seq.	109	1000	1389
Max len. of seq.	3085	9999	29700
Med. len. of seq.	877	2102	2683
Min size of image	(720,480)	(202,224)	(240,320)
Max size of image	(1280,720)	(1280,720)	(1280,720)
Med. size of image	(1280,720)	(1280,720)	(1280,720)
Absence(No. of seq, ratio)	(33, 7.1%)	(89, 2.6%)	(24, 15.1%)

Method (Robustness/Precision)	UAV123[2]	LaSOT [3]	VOT2018-LT [4]
gSiam (Proposed)	**0.595**	**0.418**	**0.484**
	0.791	**0.447**	**0.554**
SiamRPN [5]	0.466	0.349	0.109
	0.696	0.253	0.113
DaSiamRPN [1]	0.489	0.388	0.251
	0.725	0.291	0.498

- Evaluation results
  - the robustness and precision improved in all attributes



The results of attribution evaluation of [2]

Our method improved robustness/precision in all attributes

III.Comparison with SOTA methods

- Prerequisites
  - Using deeper feature extraction model than Experiment II (Alex18 -> Res50)
- Evaluation results
  - Outperformed SOTA methods on all datasets for the robustness
  - More effective for dataset with more absences of the target

Method (Robustness/Precision)	UAV123 [2]	LaSOT [3]	VOT2018-LT [4]
gSiamR (Proposed)	**0.602**	**0.501**	**0.547**
	0.808	0.490	0.606
SiamRPN++ [6]	0.600	0.495	0.424
	0.775	**0.493**	**0.647**
SiamMask [7]	**0.602**	0.467	0.426
	0.775	0.469	0.636

Our method is effective even compared with SOTA methods

Conclusions

- We developed a more suitable method for long-term tracking
  - ➤ Improved 21.7% for robustness by proposed 2 frameworks
  - ➤ 3 times faster (95.7 FPS) than a video capture speed
  - ➤ Outperformed conventional/SOTA methods for the robustness

[1] Z. Zhu et al. "Distractor-aware siamese networks for visual object tracking," ECCV2018
[2] M. Mueller et al. "A benchmark and simulator for uav tracking," ECCV2016
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[4] M. Kristan, "The sixth visual object tracking vot2018 challenge results," ECCV2018
[5] B. Li et al. "High performance visual tracking with siamese region proposal network," CVPR2018
[6] B. Li et al. "Siamrpn++:Evolution of siamese visual tracking with very deep networks," CVPR2019
[7] Q. Wang et al. "Fast online object tracking and segmentation: A unifying approach," CVPR2019

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