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JEAN KUNTZMANN
MATHÉMATIQUES APPLIQUÉES - INFORMATIQUE

Towards Robust Visual Object Tracking: Proposal Selection & Occlusion Reasoning

Yang HUA

PhD Defense, June 10 2016

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Co-encadrant de these	Dr. Karteek ALAHARI

Motivation

- Emerging technologies which require robust object tracking
  - Microsoft HoloLens

Image courtesy of Microsoft (https://www.microsoft.com/microsoft-hololens/en-us)

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- Emerging technologies which require robust object tracking
  - Google Self-Driving Car

Image courtesy of Google (https://www.google.com/selfdrivingcar/)

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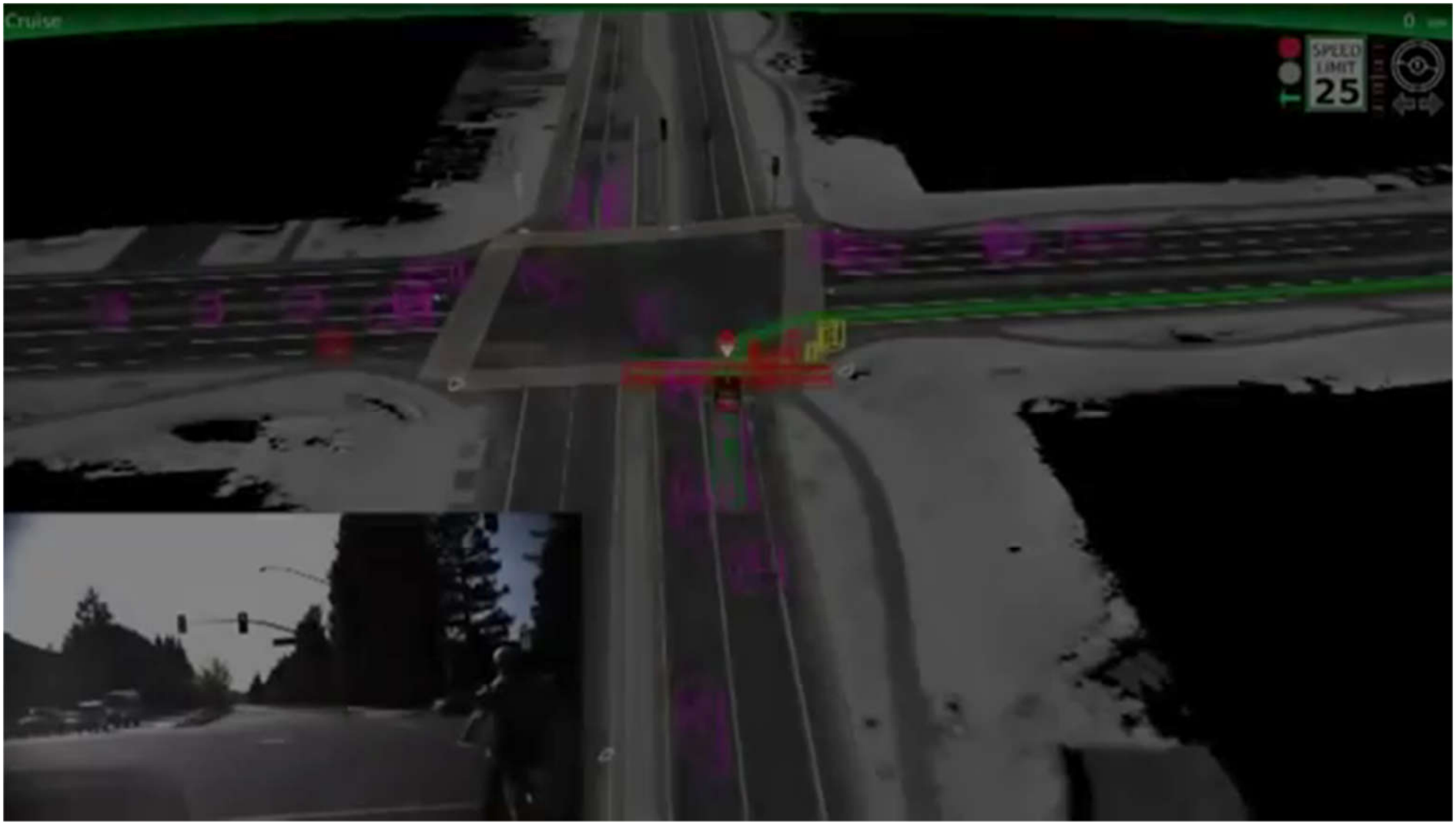

Video courtesy of Google (https://www.google.com/selfdrivingcar/)

Motivation

- Emerging technologies which require robust object tracking
  - HEXO+ Drone

Image courtesy of HEXO+ (https://hexoplus.com/)

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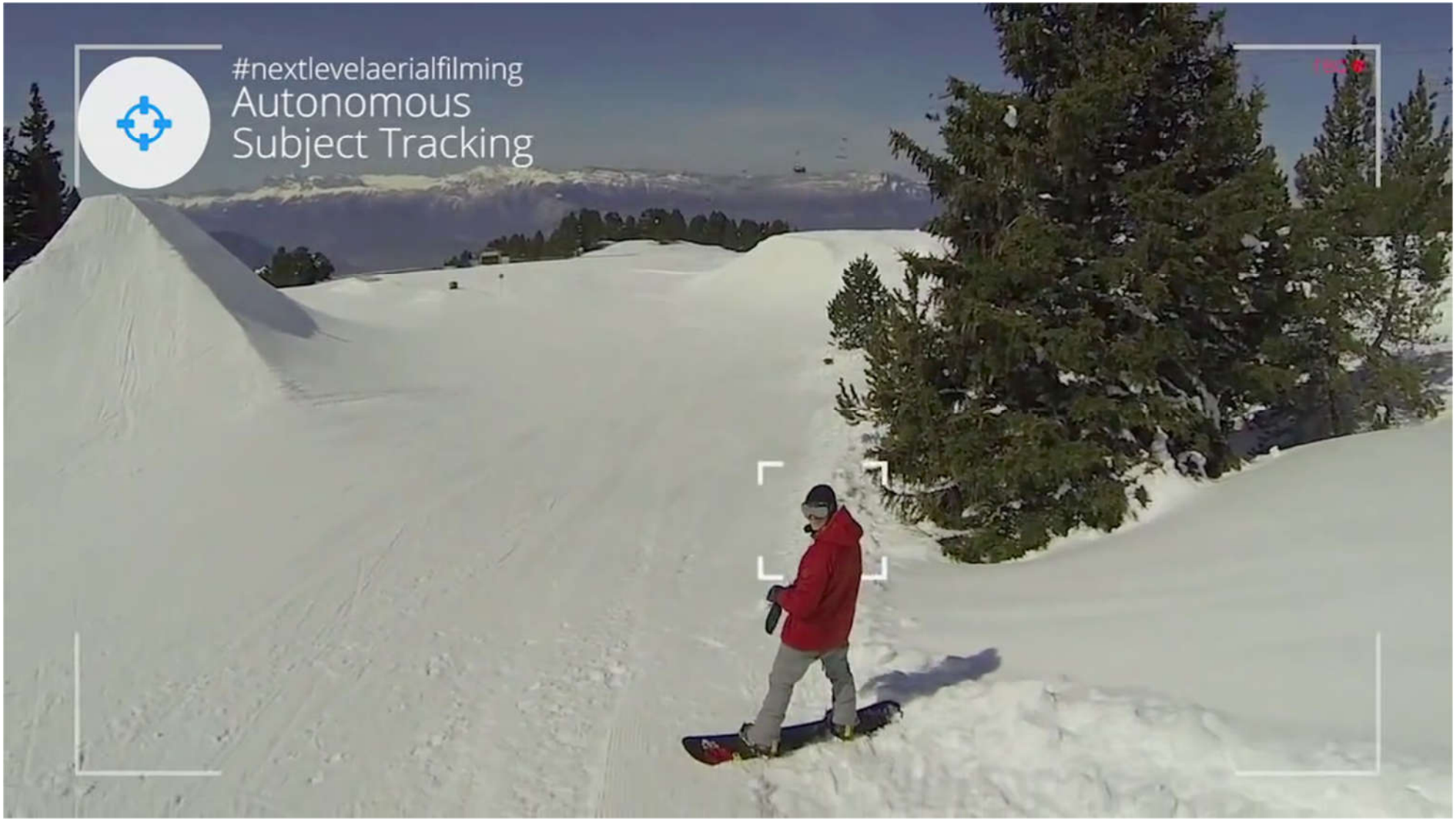

Video courtesy of HEXO+ (https://hexoplus.com/)

Visual Object Tracking

- "… the problem of estimating the **trajectory** of an object in the image plane **as it moves around a scene**" [Yilmaz'06]
- Setup: initial object position is defined at the beginning of a video

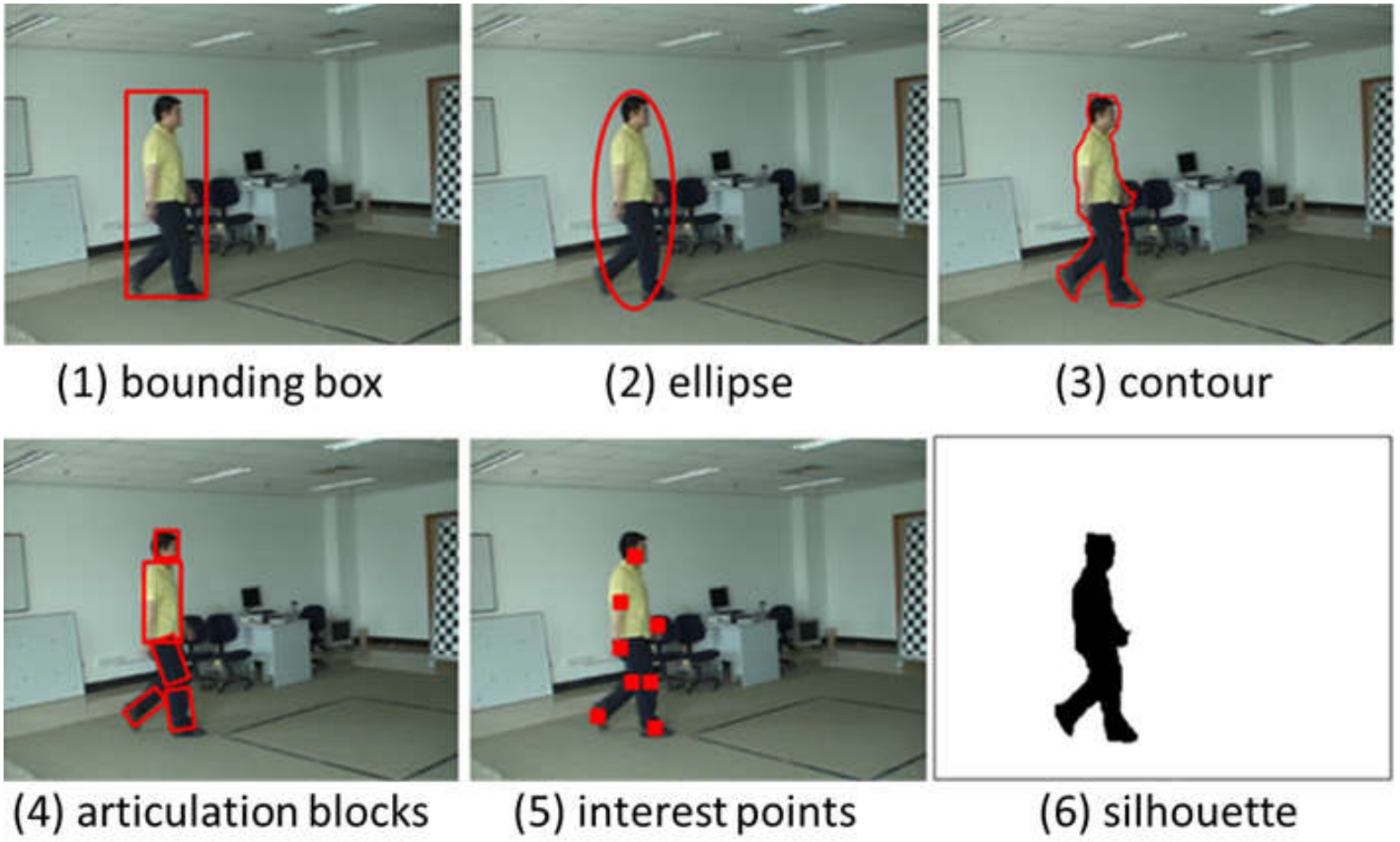

Image courtesy of [Li'13]

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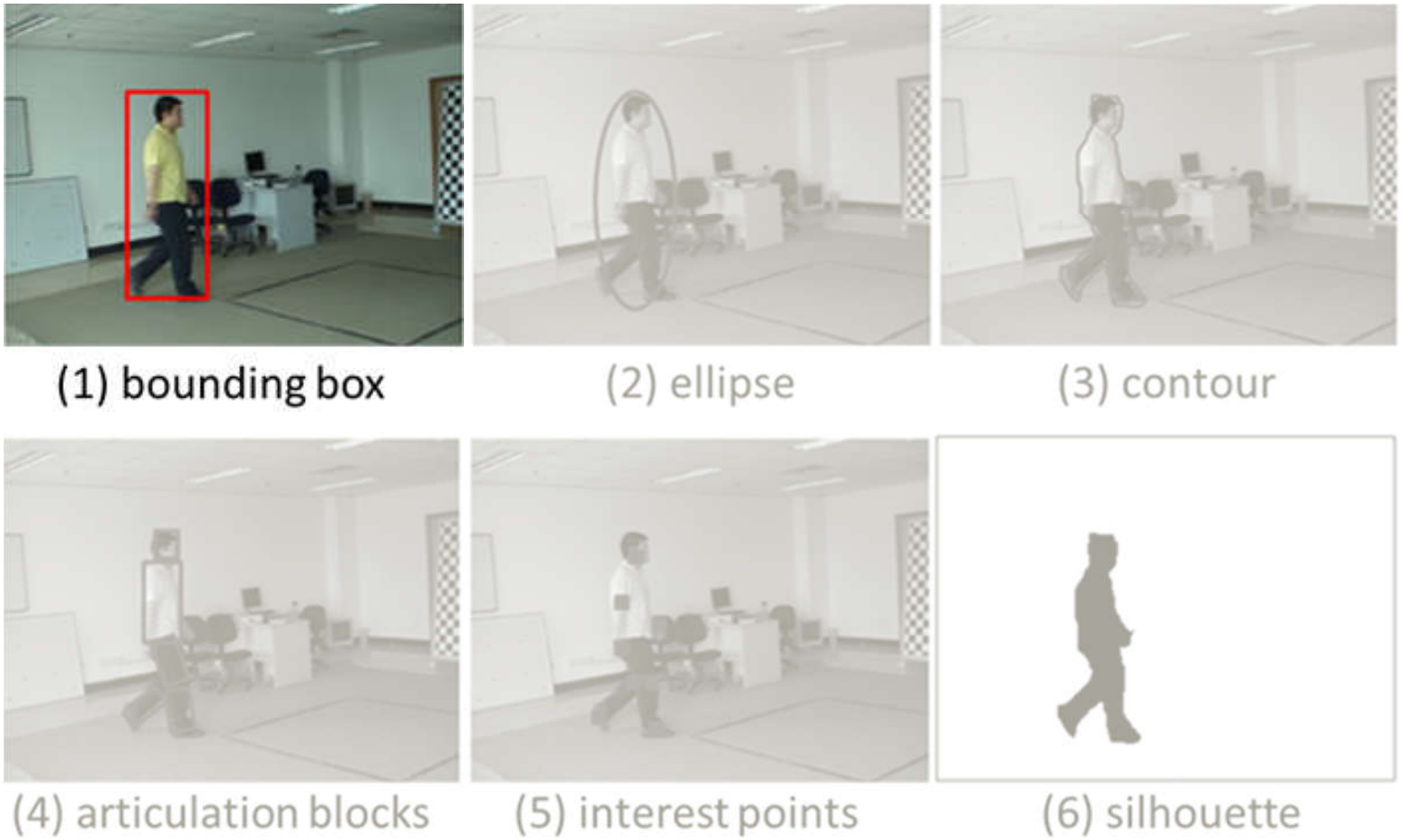


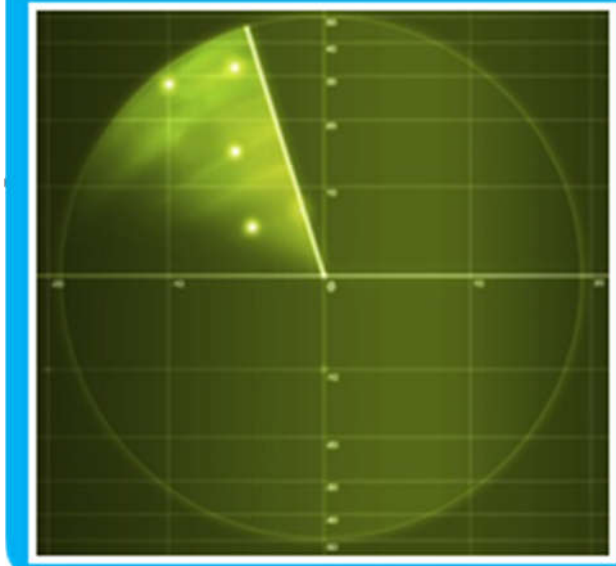
Image courtesy of [Li'13]

Visual Object Tracking: A brief history

1950s

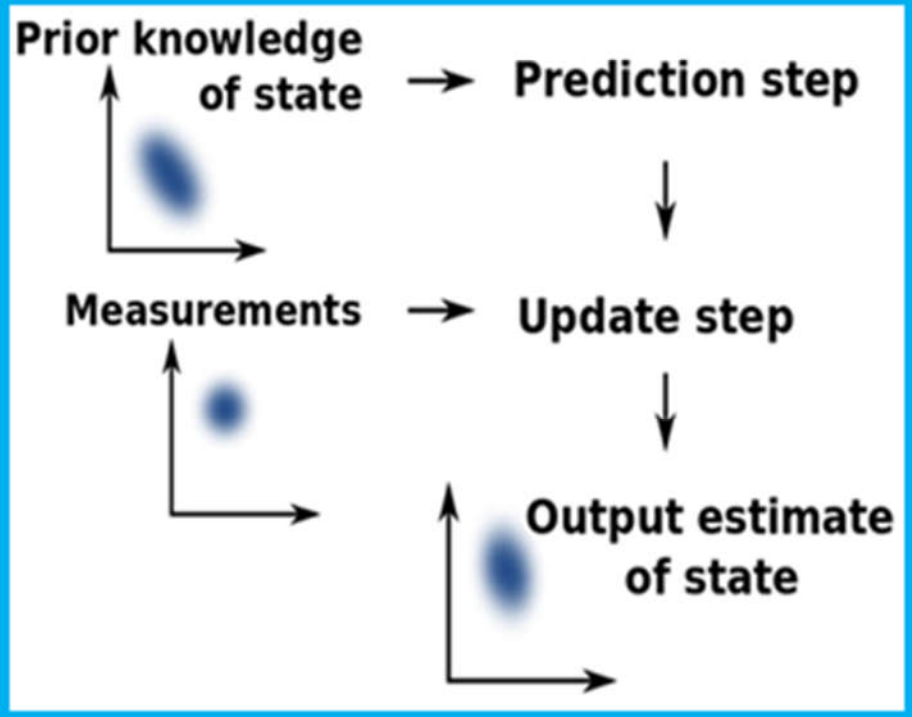
RADAR

[Wax, 1955]



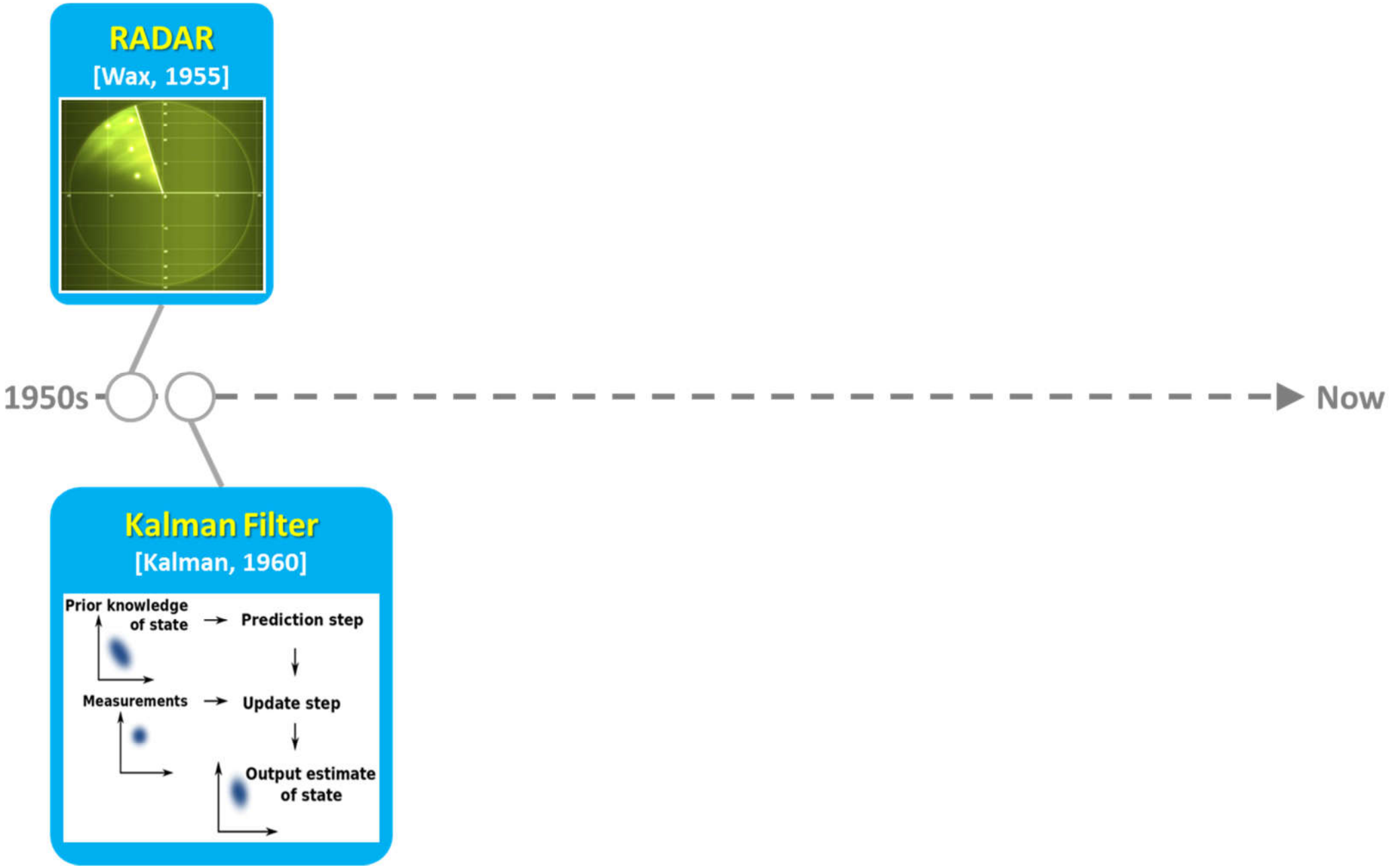
Kalman Filter

[Kalman, 1960]



Now

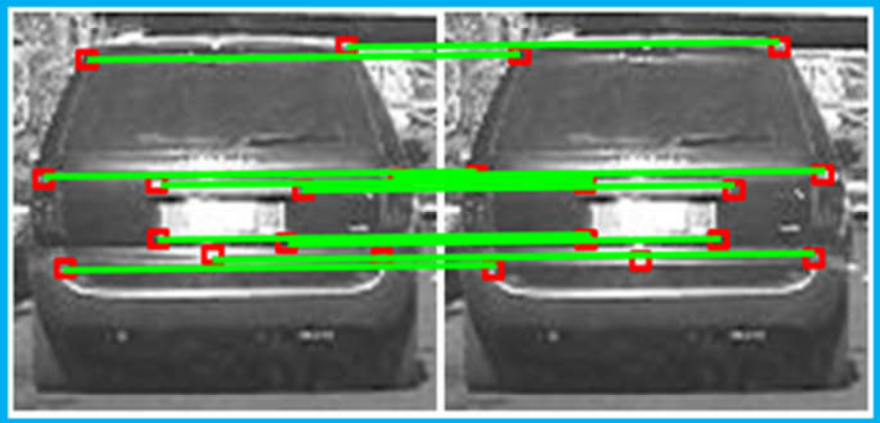
Visual Object Tracking: A brief history



Visual Object Tracking: A brief history

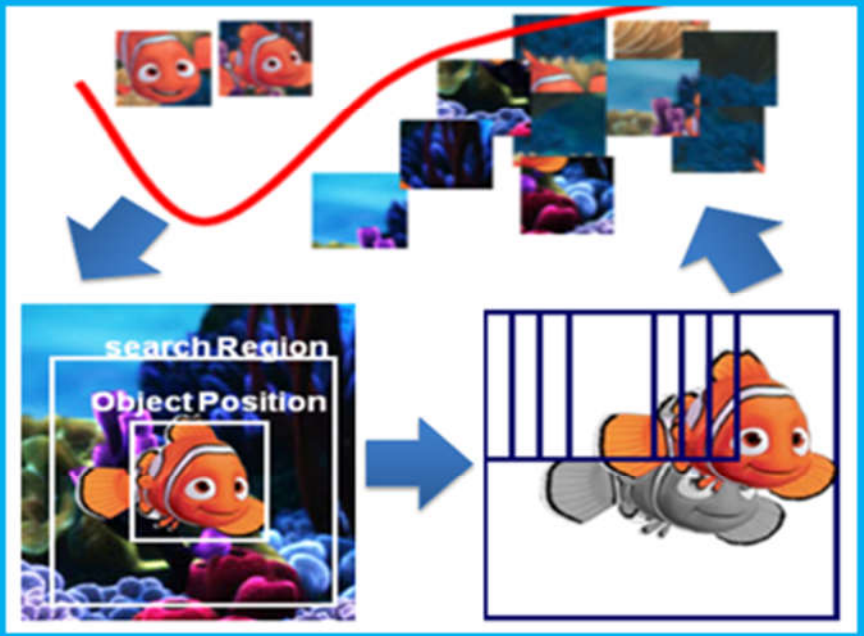
Tracking-By-Detection Template matching

[Lucas and Kanade, 1981, Tomasi and Kanade, 1991]



Tracking-By-Detection Discriminative modeling

[Avidan, 2004, Grabner et al., 2006, Hare et al., 2011]



Visual Object Tracking: A brief history

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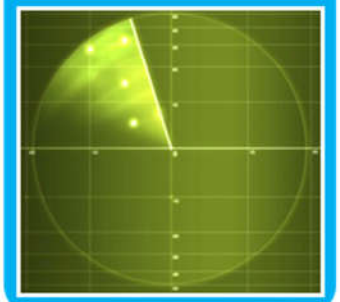

1950s ---------- Now

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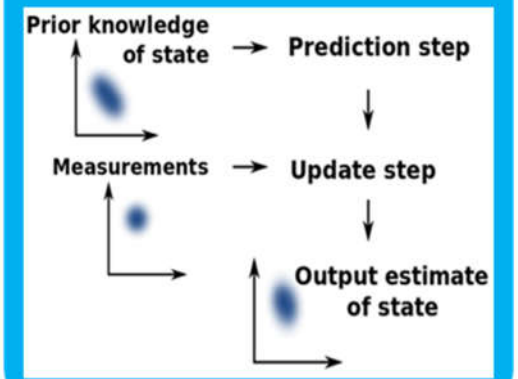

Tracking-By-Detection
Template matching
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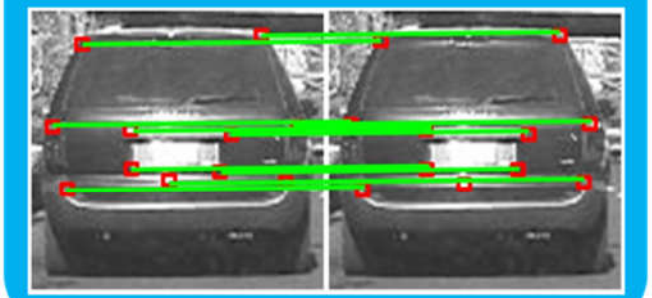

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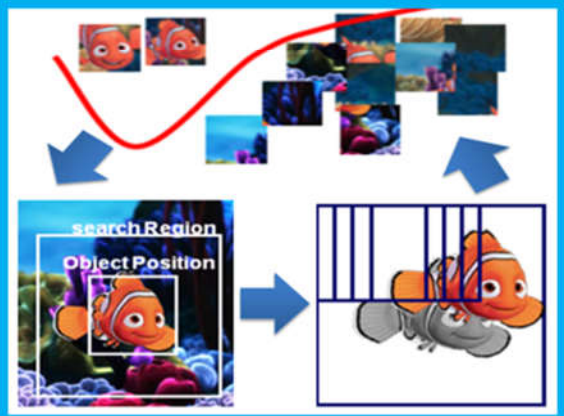
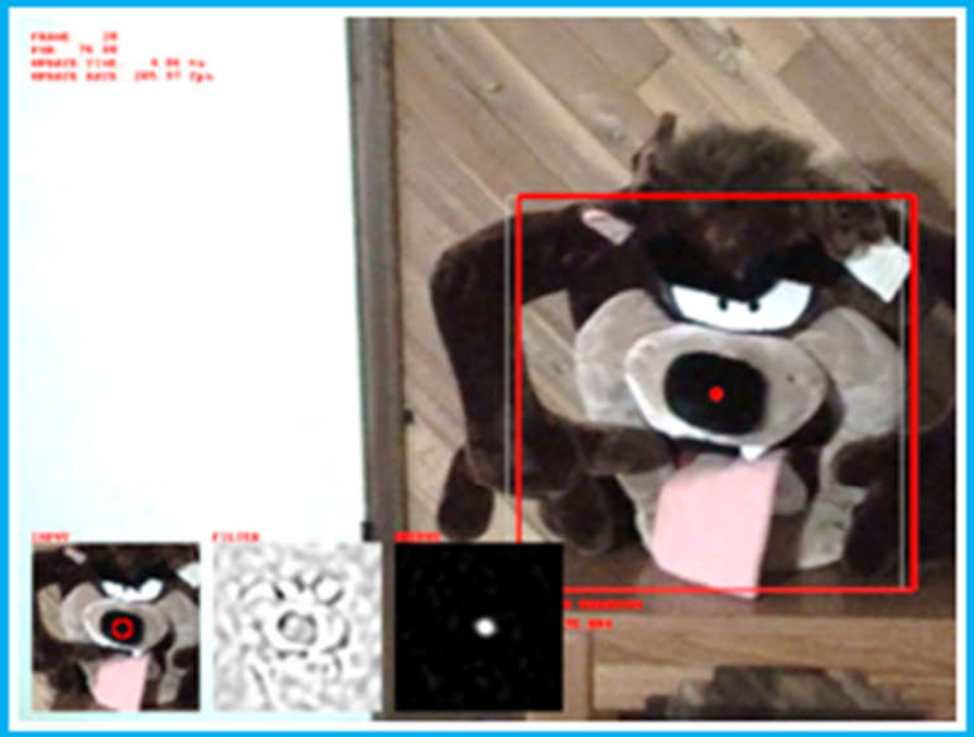


Visual Object Tracking: A brief history

Correlation Filters

[Bolme et al., 2010,
Henriques et al., 2015]



Visual Object Tracking: A brief history

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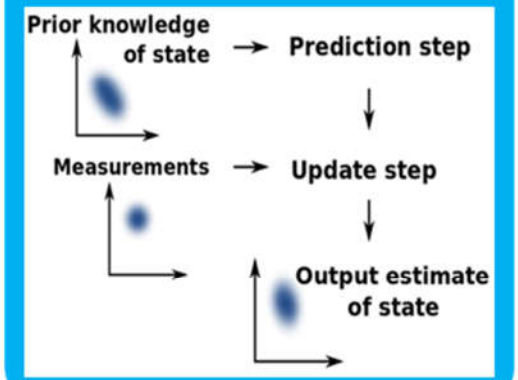

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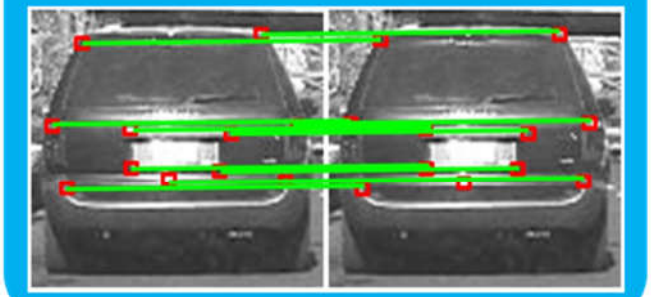

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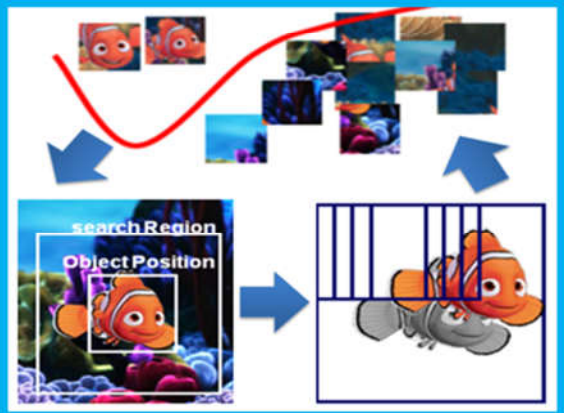


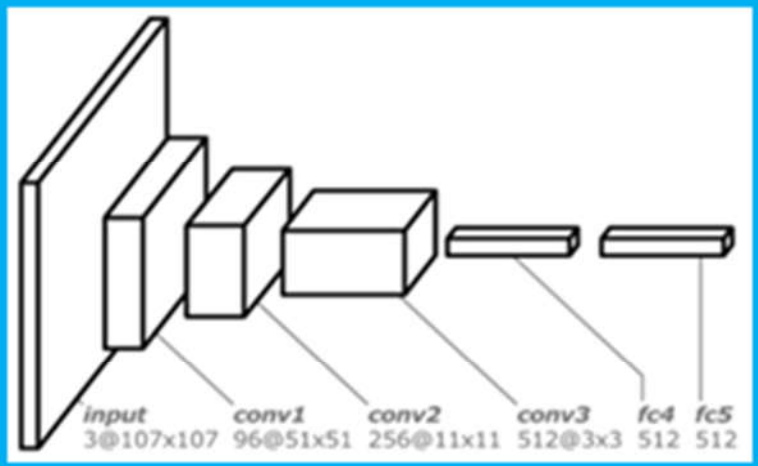
Visual Object Tracking: A brief history

Tracking Dataset & Challenge

[Wu et al., 2013, Kristan et al., 2013]

Deep Learning for Tracking

[Nam & Han, 2016]



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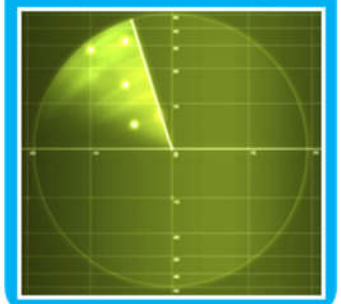

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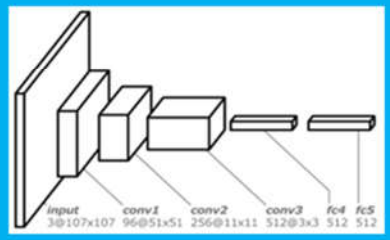

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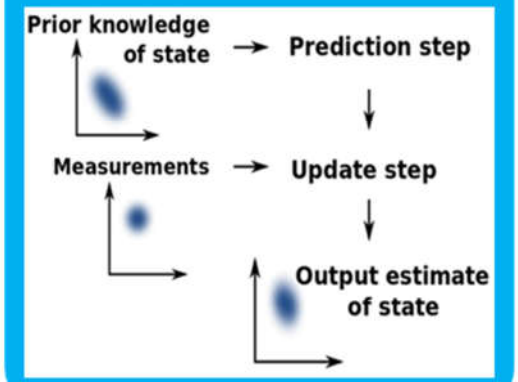

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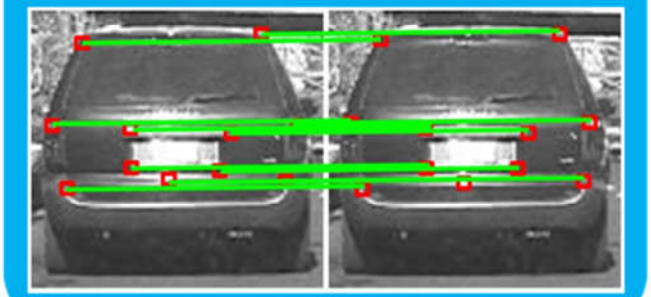

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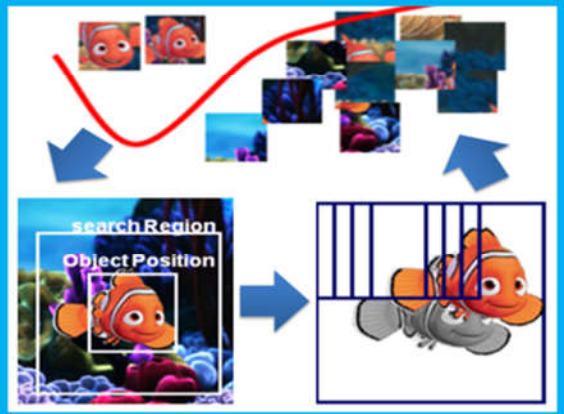


Visual Object Tracking: Applications

- Plays a fundamental role for high-level computer vision tasks
  - Video segmentation [Li'13]

Image courtesy of [Li'13]

Visual Object Tracking: Applications

- Plays a fundamental role for high-level computer vision tasks
  - Action localization [Weinzaepfel'15]

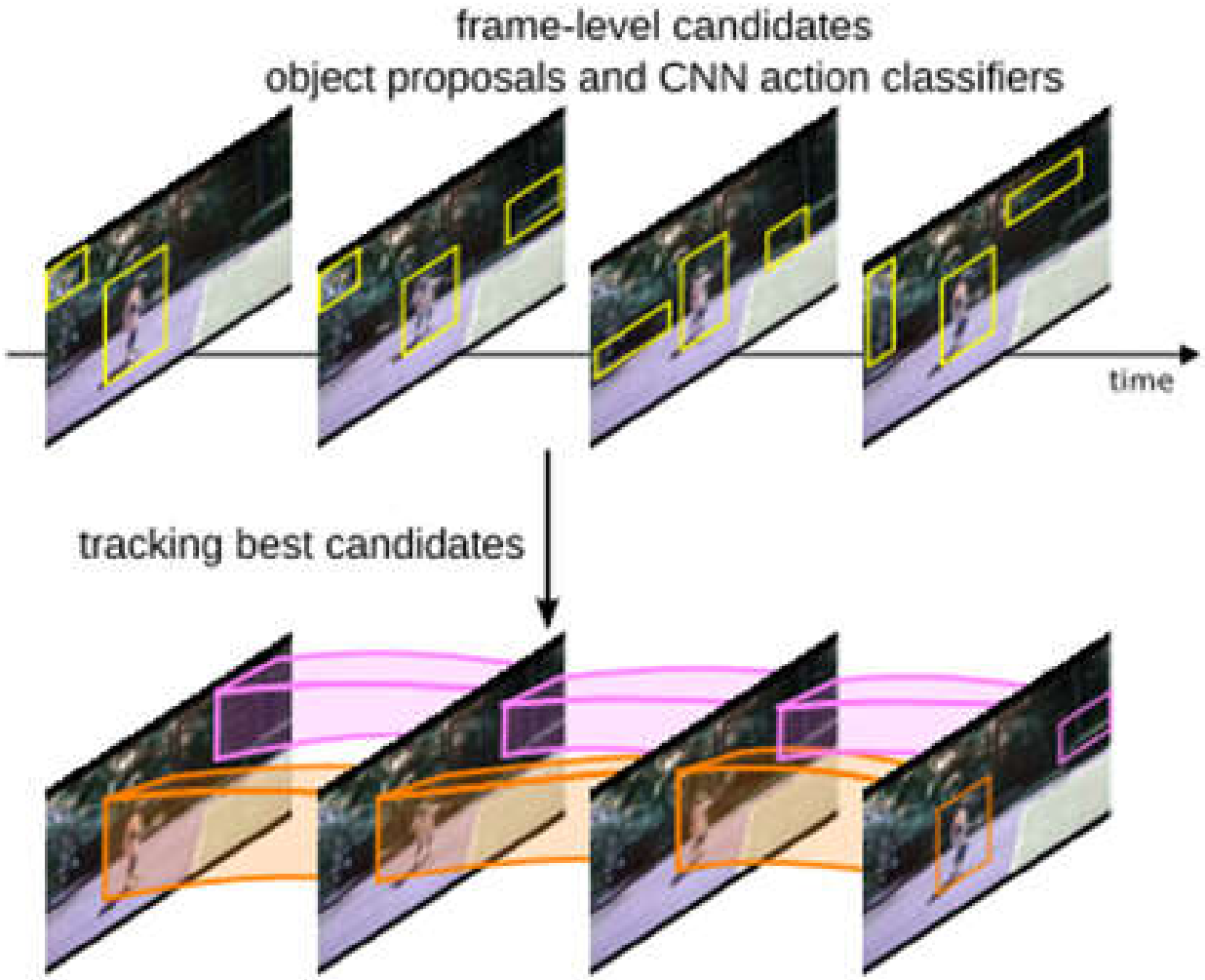
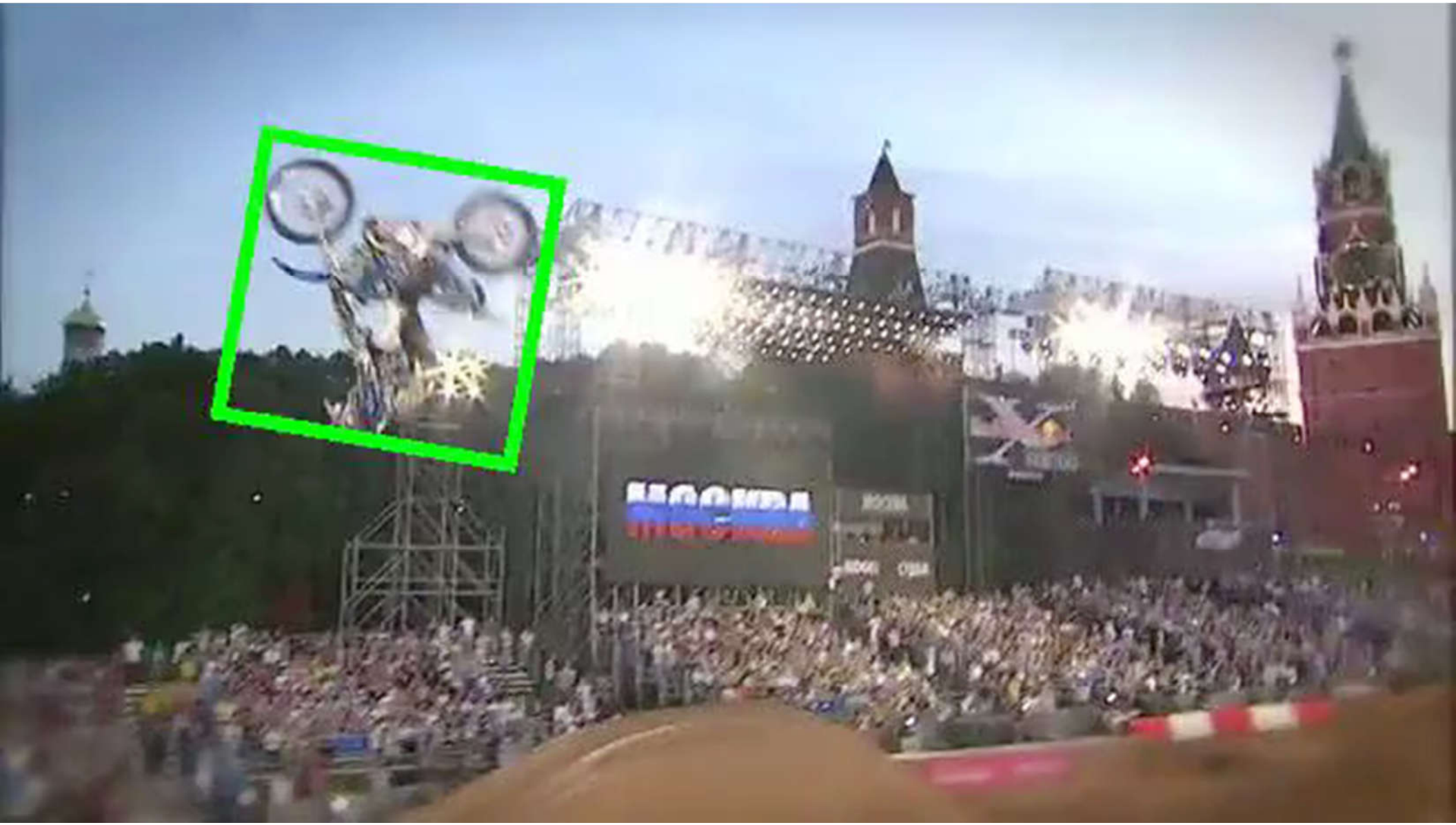


Image courtesy of [Weinzaepfel'15]

Challenge: Significant Transformations



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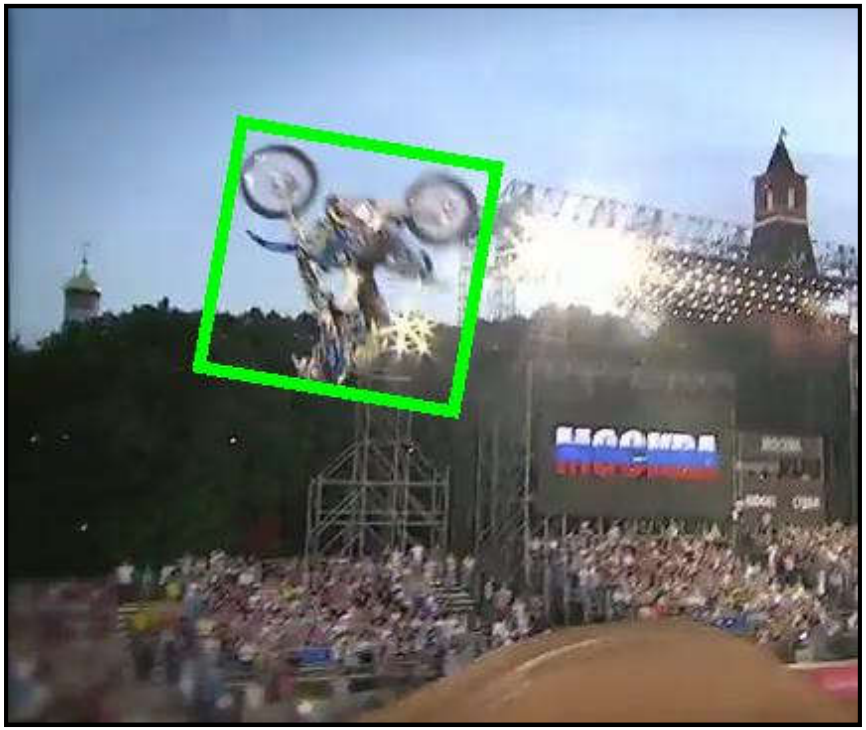








Challenge: Occlusion or Leaving/Re-entering the Field-of-View

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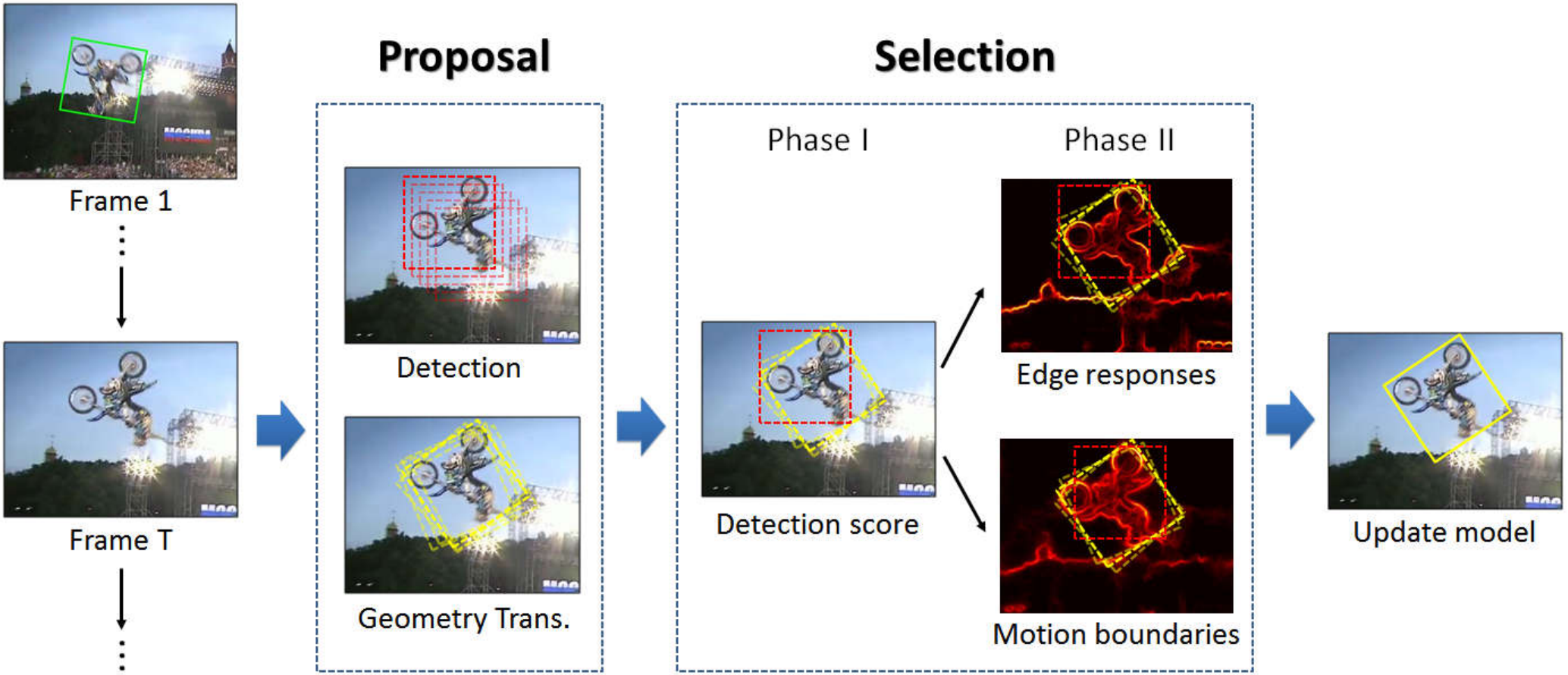
Contributions of this thesis

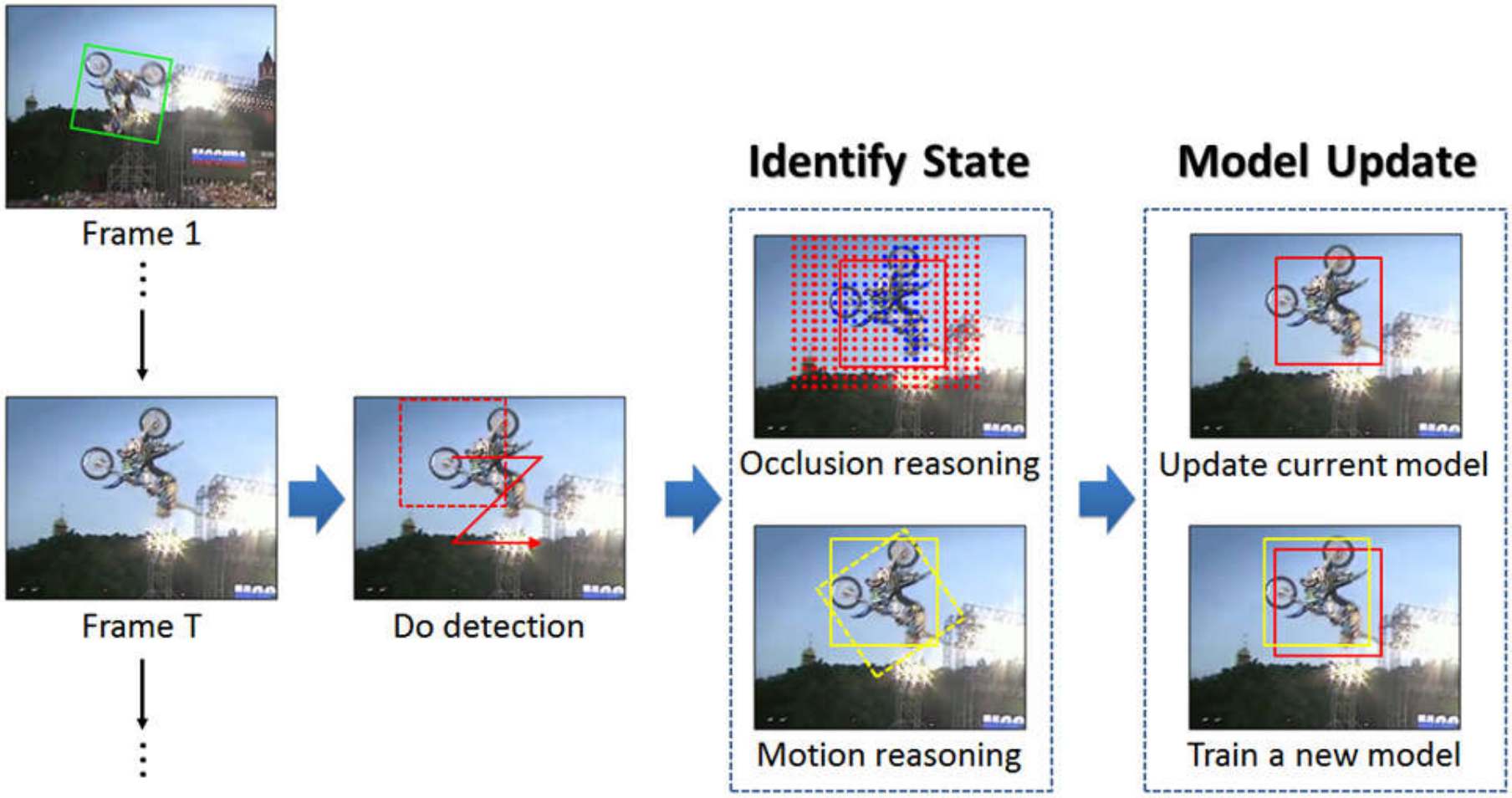
- Proposal and selection framework for short-term tracking



- Publication: Y. Hua, K. Alahari, and C. Schmid. Online object tracking with proposal selection. In ICCV, 2015
- Award: “Winning tracker” in the VOT-TIR2015 challenge

Contributions of this thesis

- Robust model update in the context of long-term tracking



- Publication: Y. Hua, K. Alahari, and C. Schmid. Occlusion and motion reasoning for long-term tracking. In ECCV, 2014

Outline

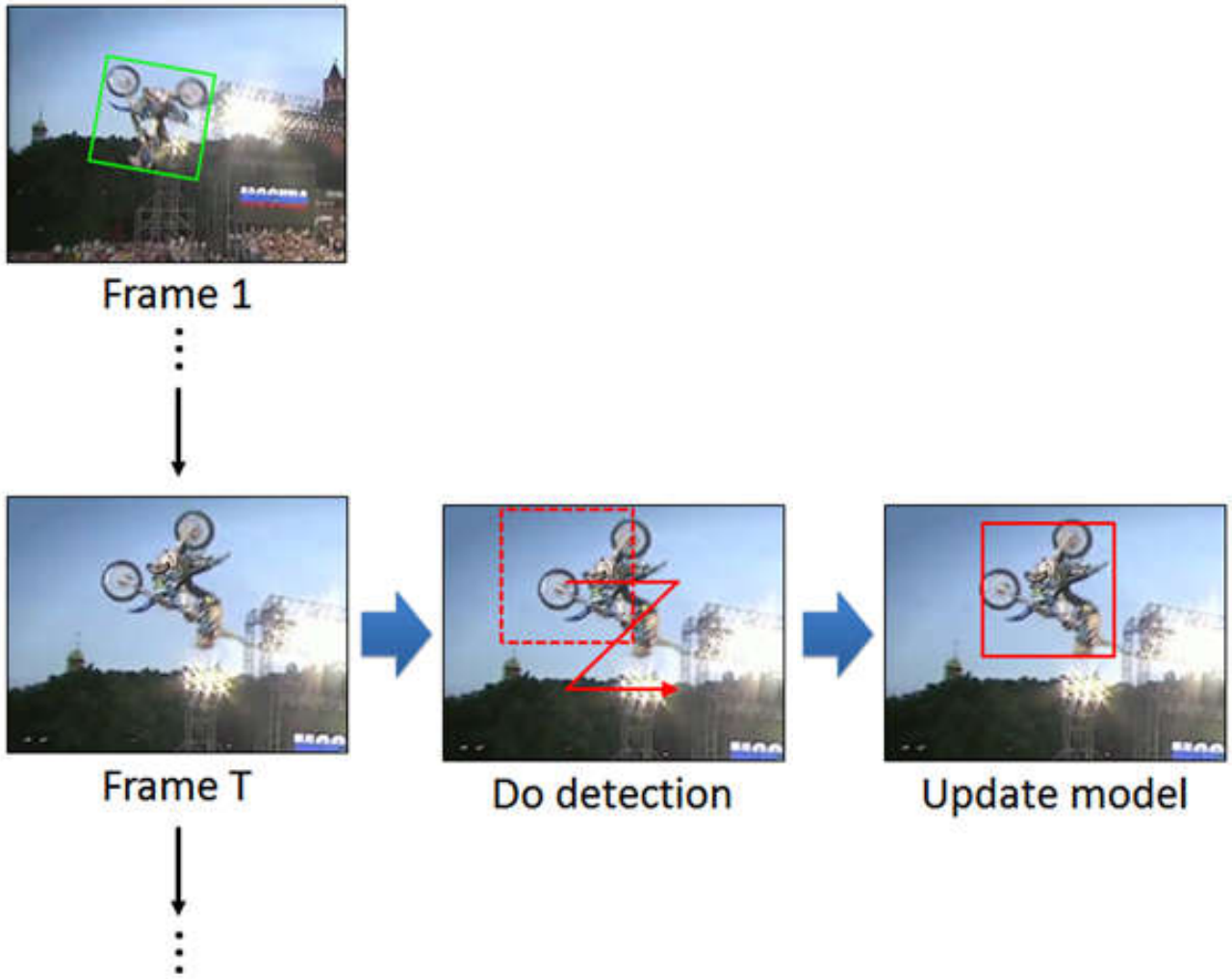
- ***Online Object Tracking with Proposal Selection***

- Occlusion and Motion Reasoning for Long-term Tracking

- Conclusion and Future Work

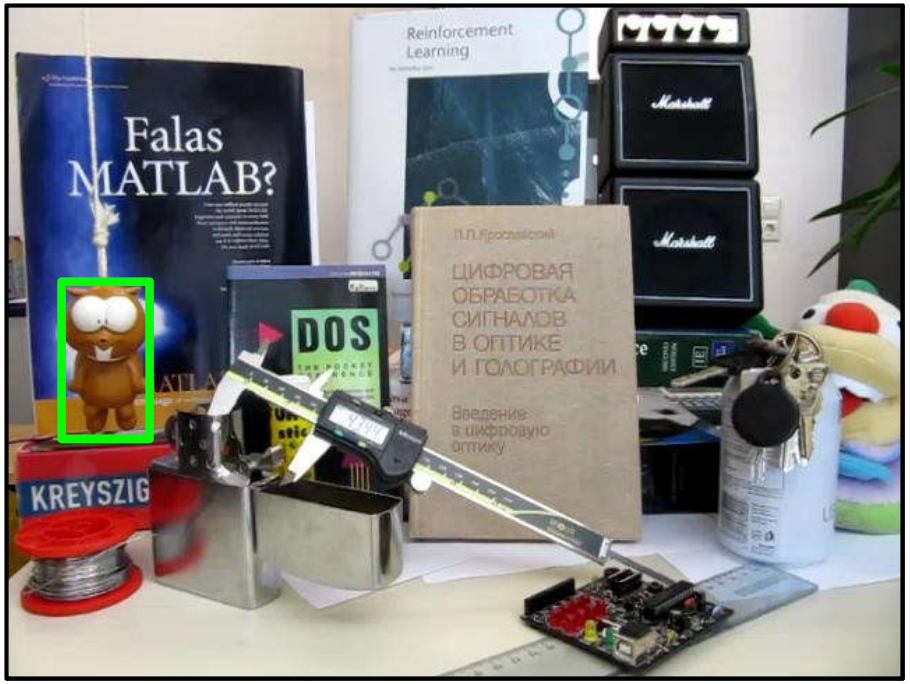
Tracking-By-Detection

- A successful approach on diverse benchmarks [Wu'13, Kristan'13/'14]
  - Structured Output Tracking with Kernels (Struck) [Hare'11]
  - Pixel based LUT Tracker (PLT) [Heng'12]
  - Discriminative Scale Space Tracker (DSST) [Danelljan'14]

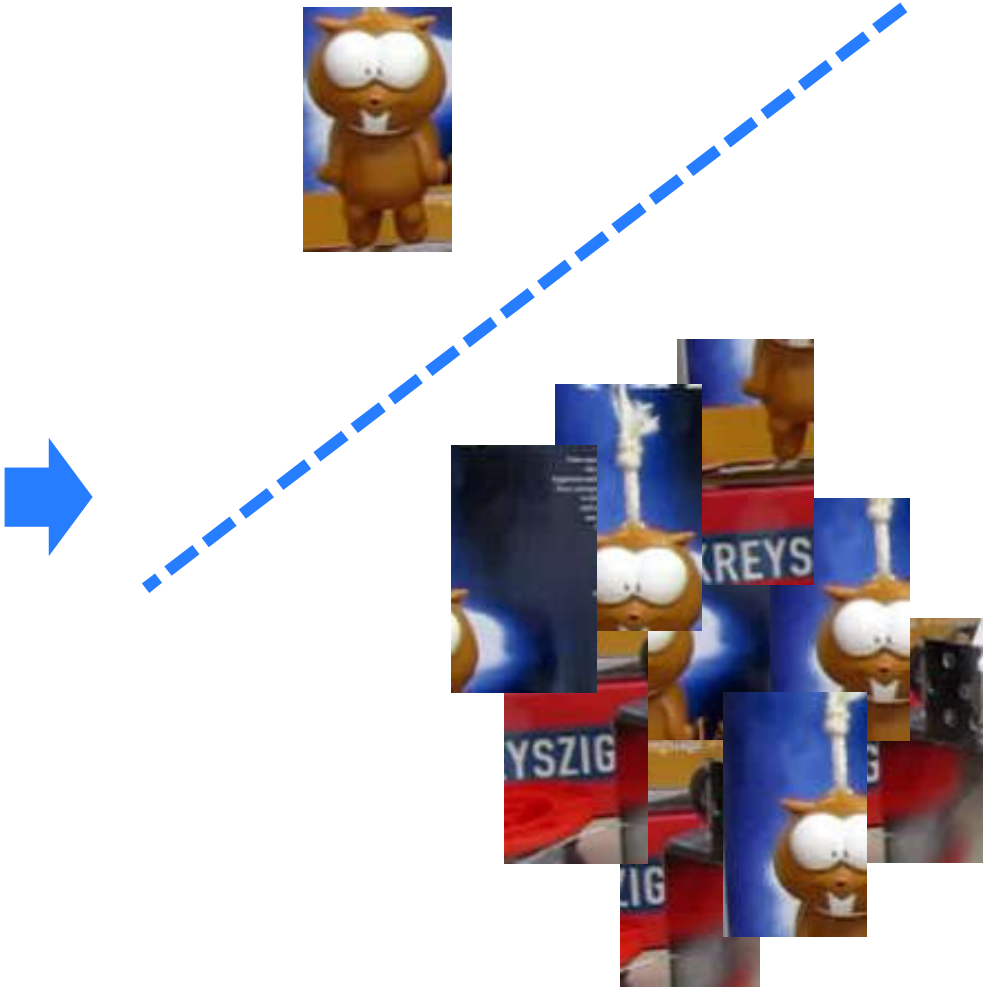


Tracking-By-Detection

- Two key points
  - Discriminative learning



Frame 1



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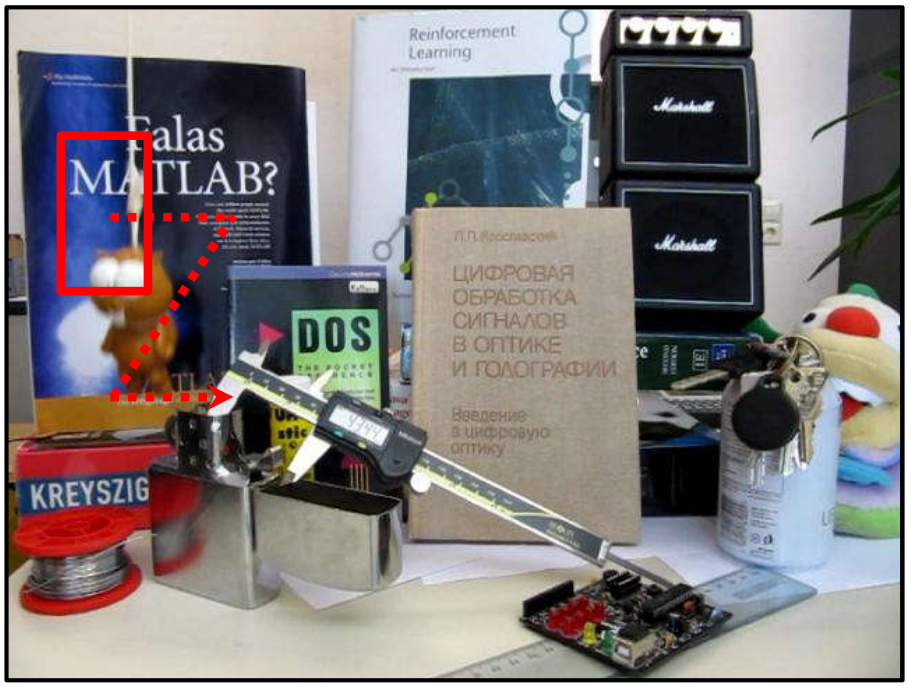


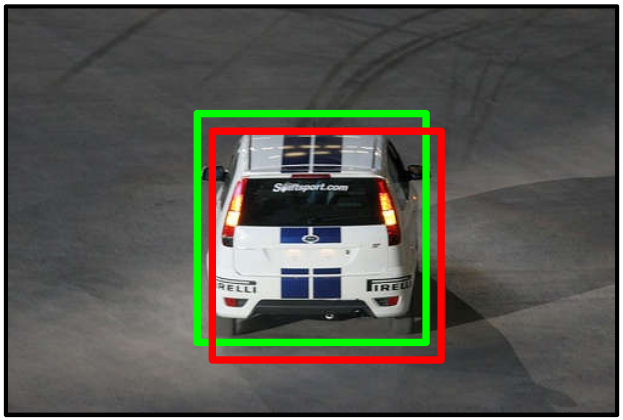
Frame 382

Similarity

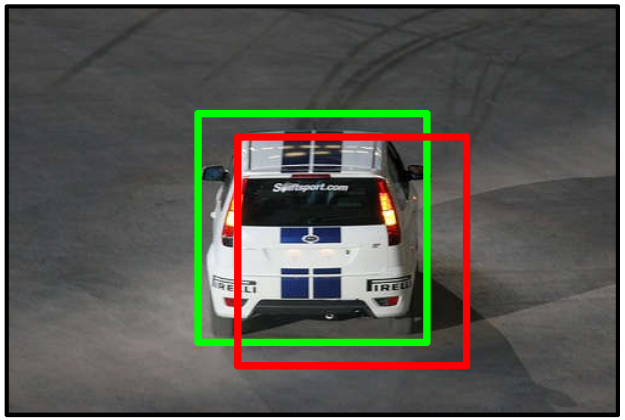
Dissimilarity

Tracking-By-Detection

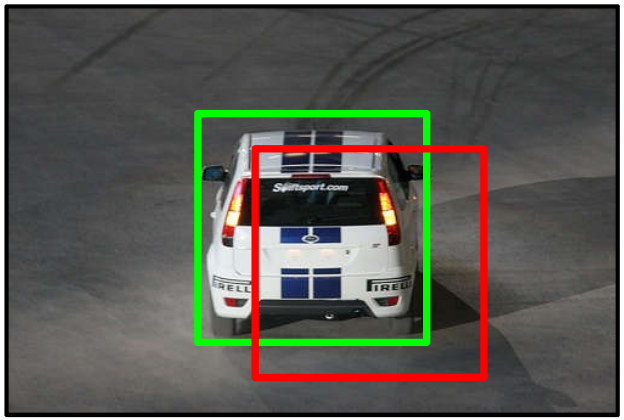
- Two key points
  - Discriminative learning
  - Pixel-accurate localization



IoU = 0.9



IoU = 0.7

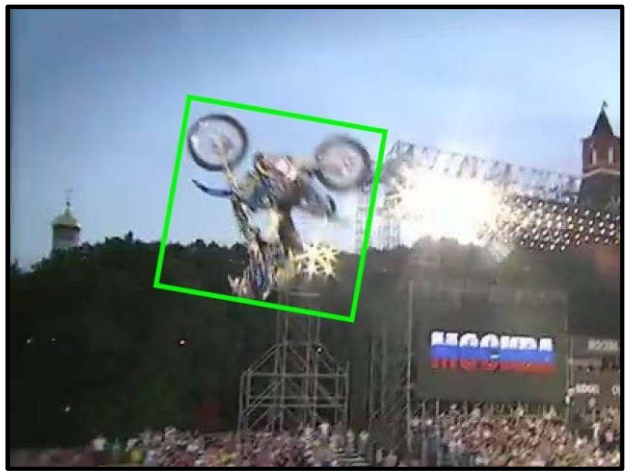


IoU = 0.5

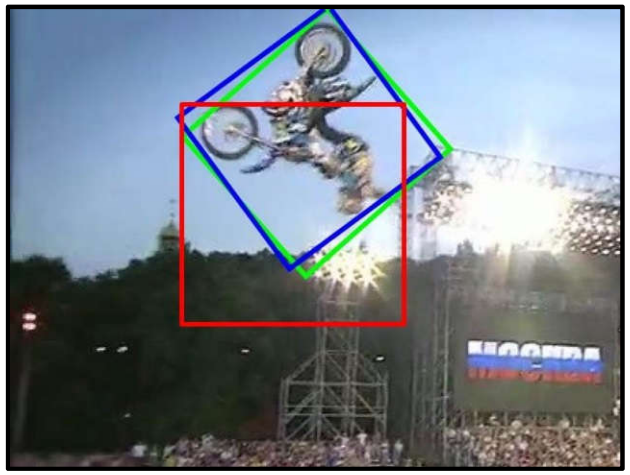
Tracking-By-Detection

- Limitations of existing methods
  - Can not handle challenging conditions where an object undergoes transformations, e.g., severe rotation
  - Select tracking results based on detection score only

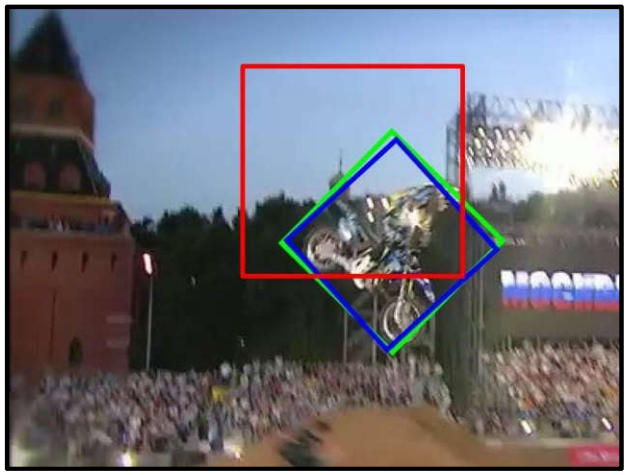
DSST Ours Groundtruth



Frame 1

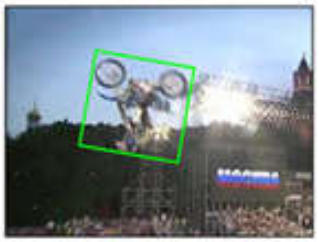


Frame 10



Frame 30

Our approach: Proposal Selection Tracking



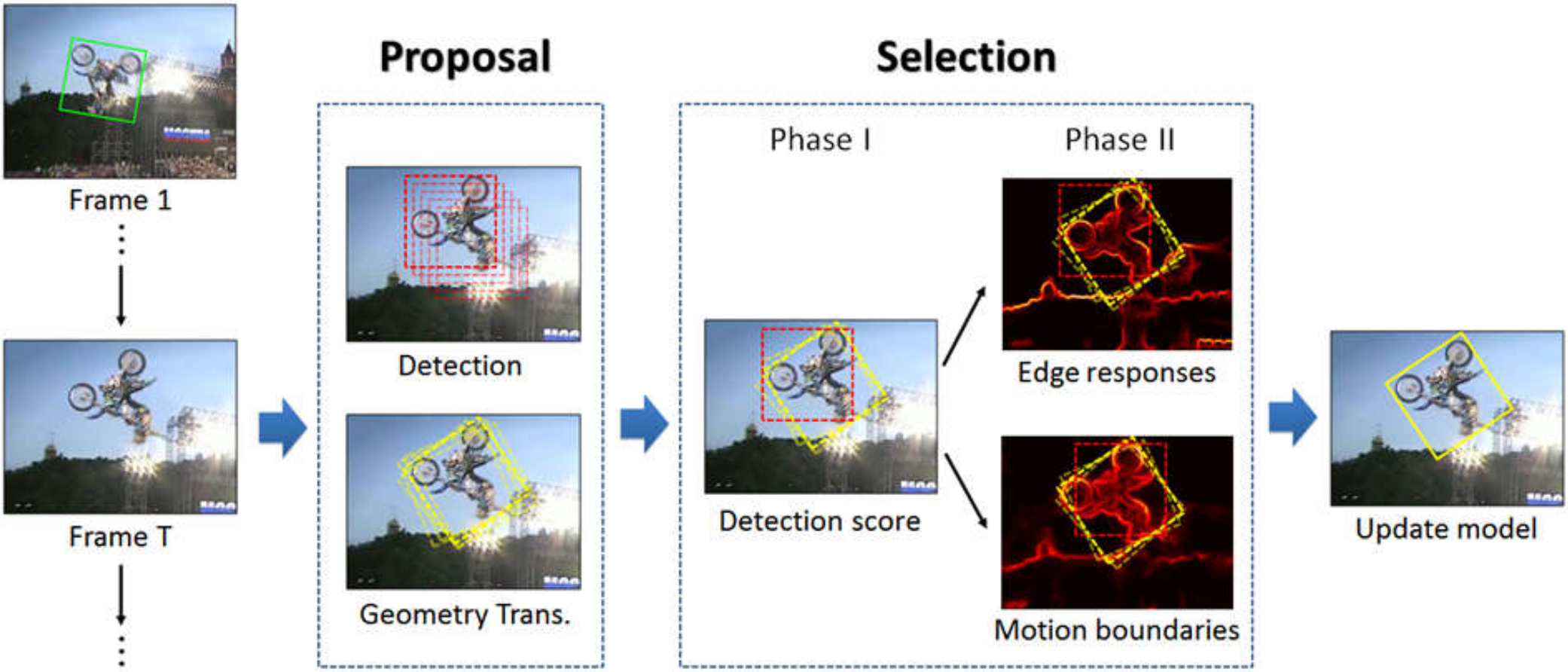
Frame 1

Frame T

Do detection

Update model

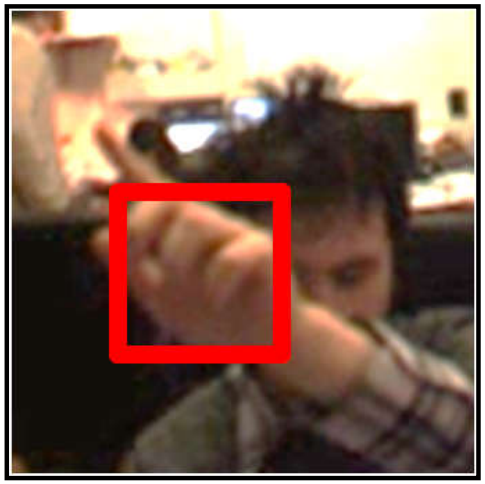
Our approach: Proposal Selection Tracking



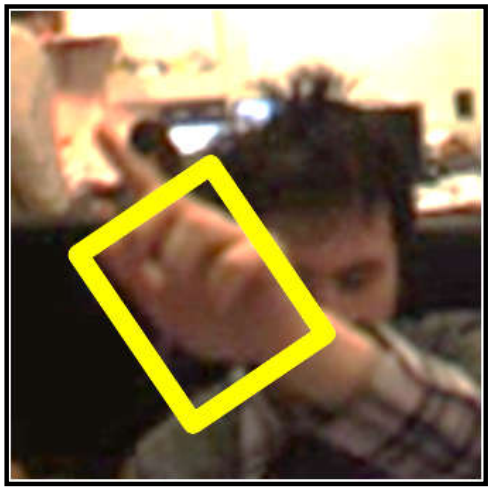
Proposals

- Detection proposals
- Geometry proposals
  - Compute frame-to-frame pixel correspondences with optical flow [Brox'11]
  - Estimate similarity transformations with Hough transform voting [Lowe'04]

Ground truth



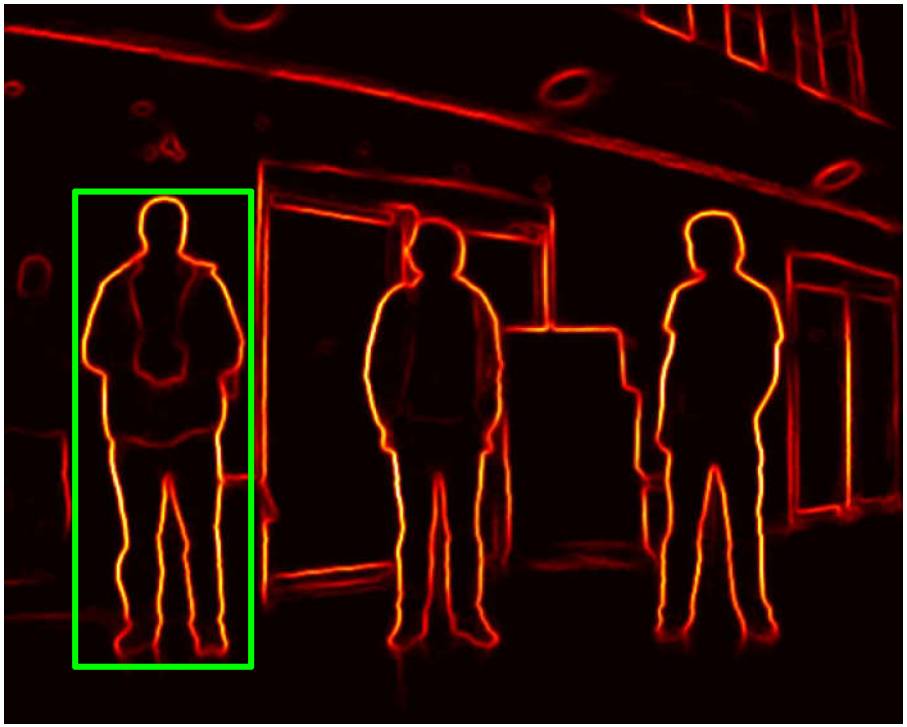
Detection proposal



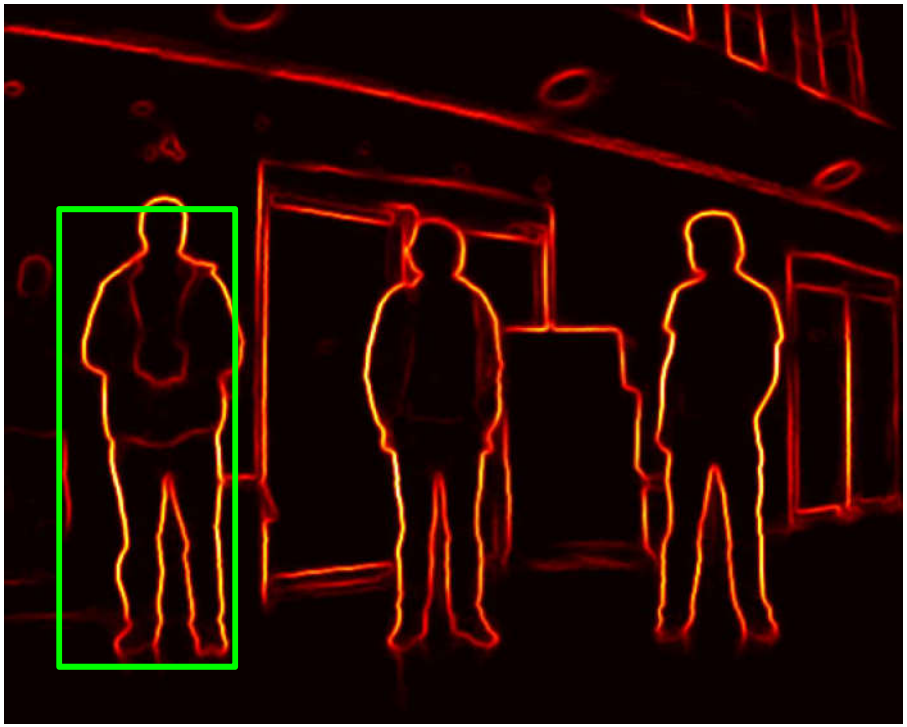
Geometry proposal

Selection

- Multiple cues for selection
  - Detection scores
  - Edgebox score [Zitnick'14], originally from edge response [Dollár'13]



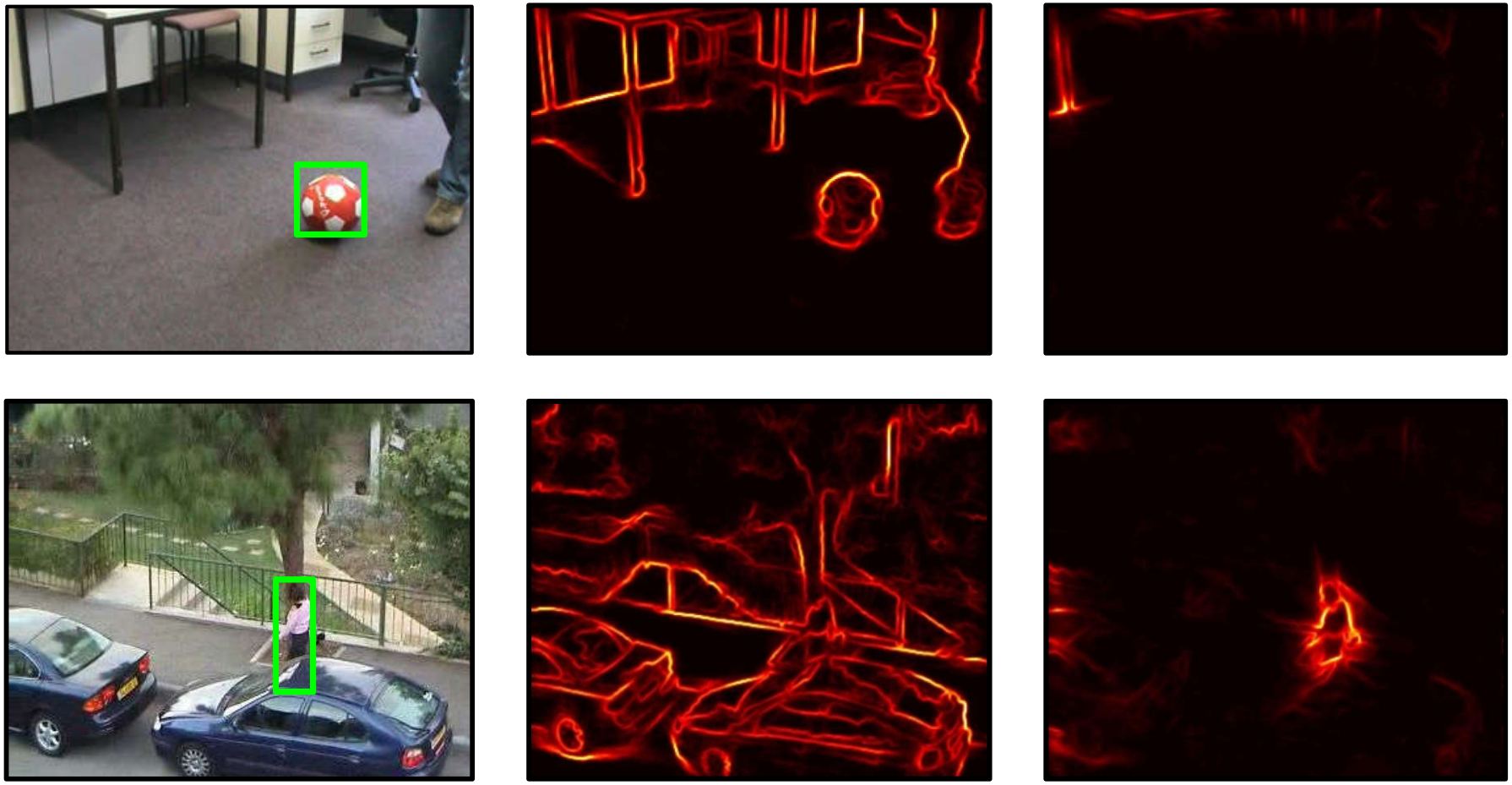
High edgebox score



Low edgebox score

Selection

- Multiple cues for selection
  - Edgebox scores from edge responses and motion boundaries [Weinzaepfel'15] are **complementary**

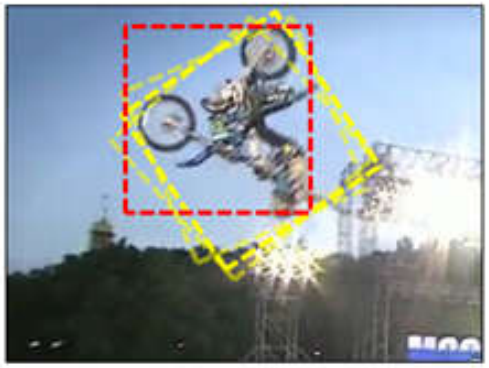


Edge Responses Motion boundaries

Selection

- How to combine multiple cues?
  - Propose a two-phase strategy

Phase I



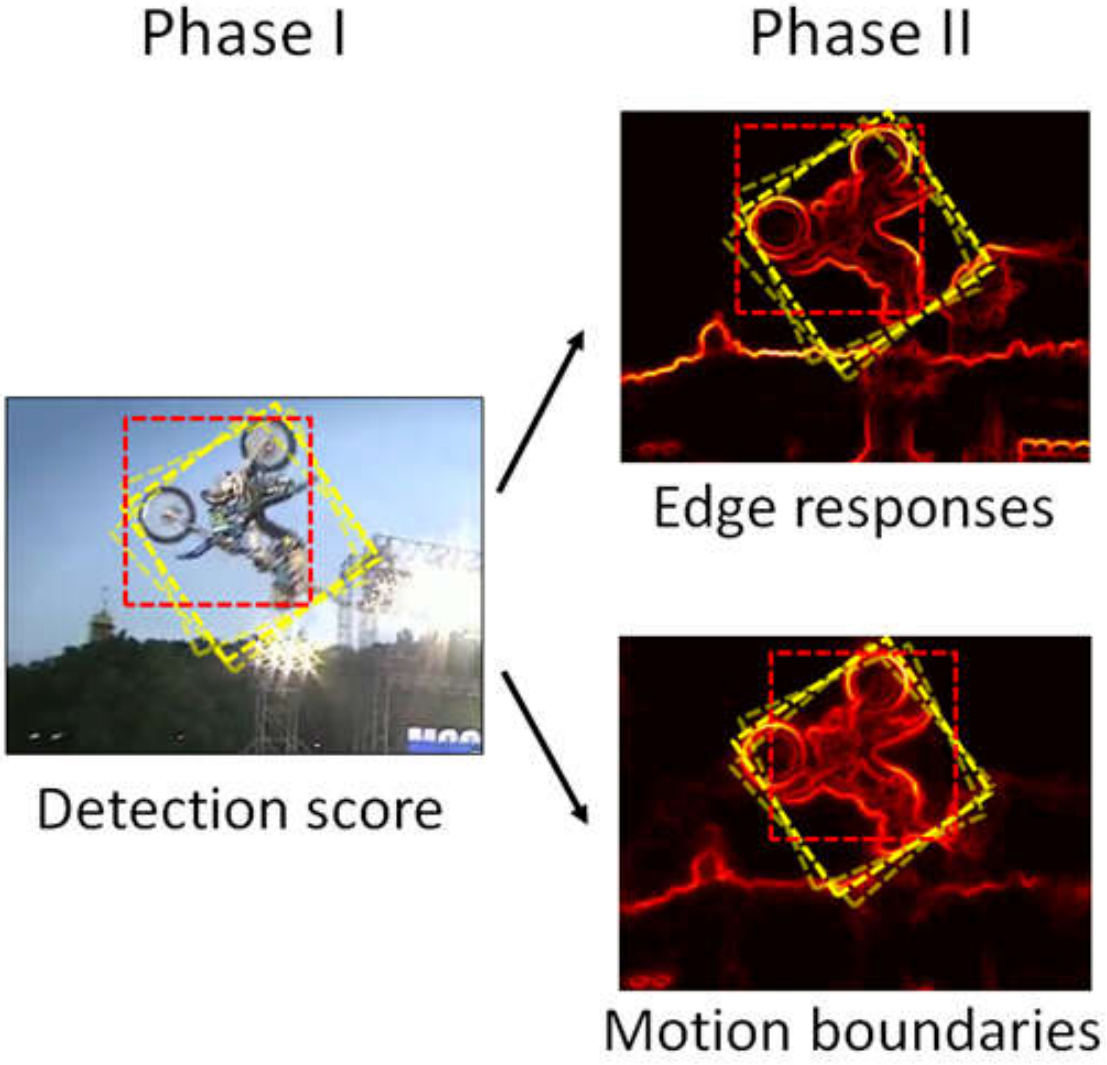
Detection score

- Phase I
  In frame t, select candidates whose detection scores (DS_i^t) are statistically similar to the best detection score (DS_{best}^t), i.e.,

$$\frac{DS_{best}^t - DS_i^t}{DS_{best}^t} < 1\%$$

Selection

- How to combine multiple cues?
  - Propose a two-phase strategy

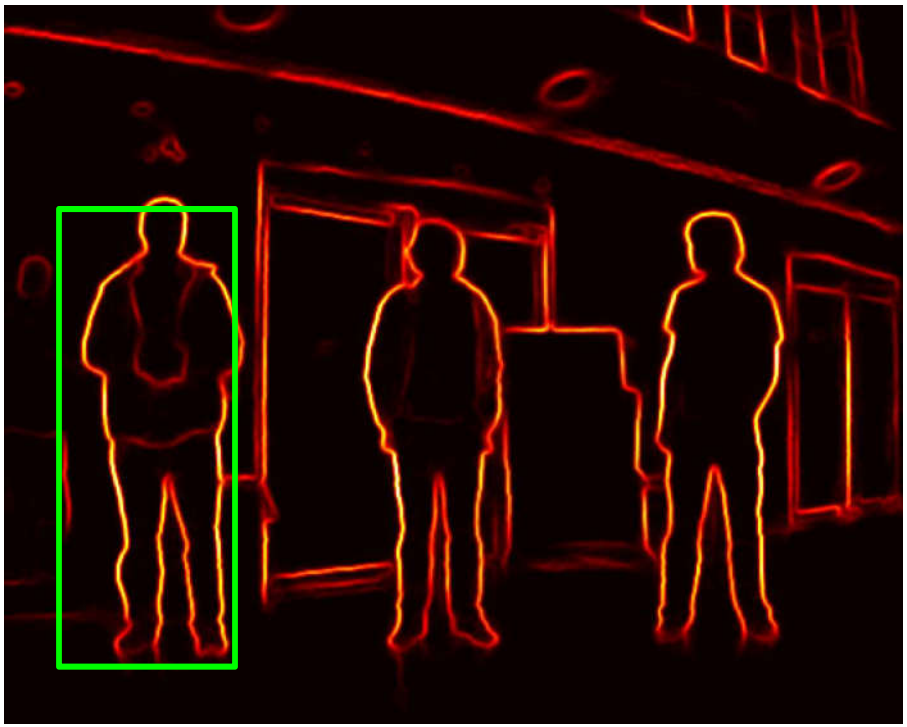


- Phase II
  Determine result with the best normalized edgebox scores from edge responses and motion boundaries

$$ES^t_{norm} = \frac{ES^t - \mu_{[t-5,t-1]}}{\sigma_{[t-5,\,t-1]}}$$

Selection

- How to combine multiple cues?
  - Need for the two-phase strategy

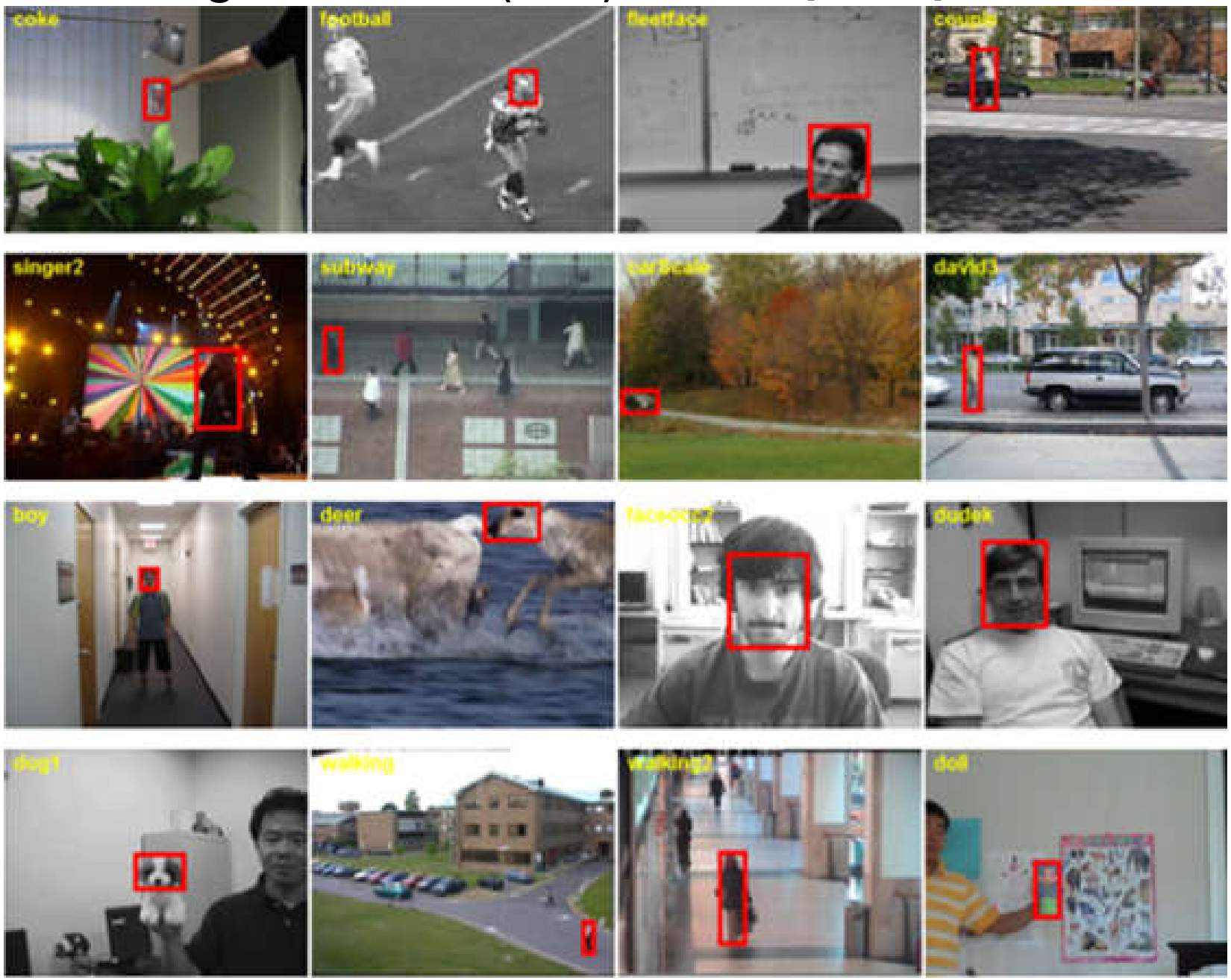


Low edgebox score, but
high detection score

High edgebox score, but
low detection score

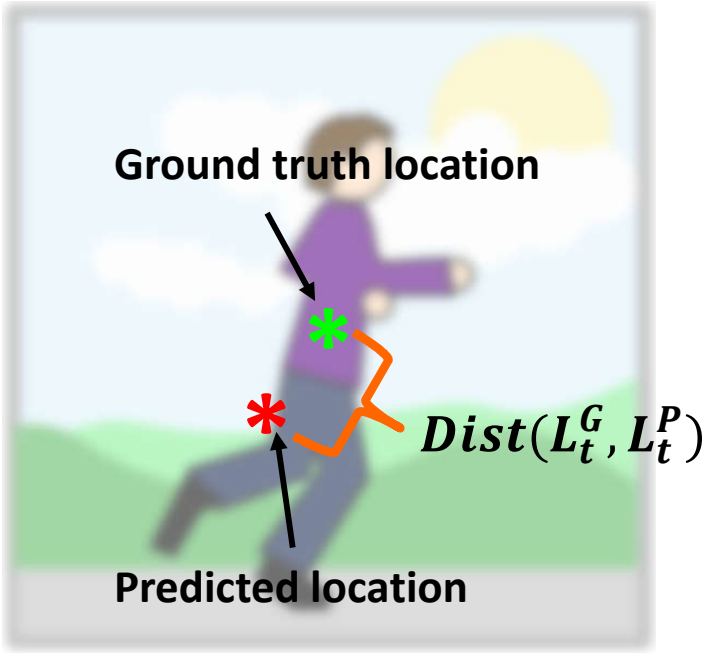
Experimental Results

- Online Tracking Benchmark (OTB) Dataset [Wu'13]



Experimental Results

- Online Tracking Benchmark (OTB) Evaluation Metrics
  - Precision Plot: Percentage of frames with location error less than threshold
  - Success Plot: Percentage of frames with overlap larger than threshold



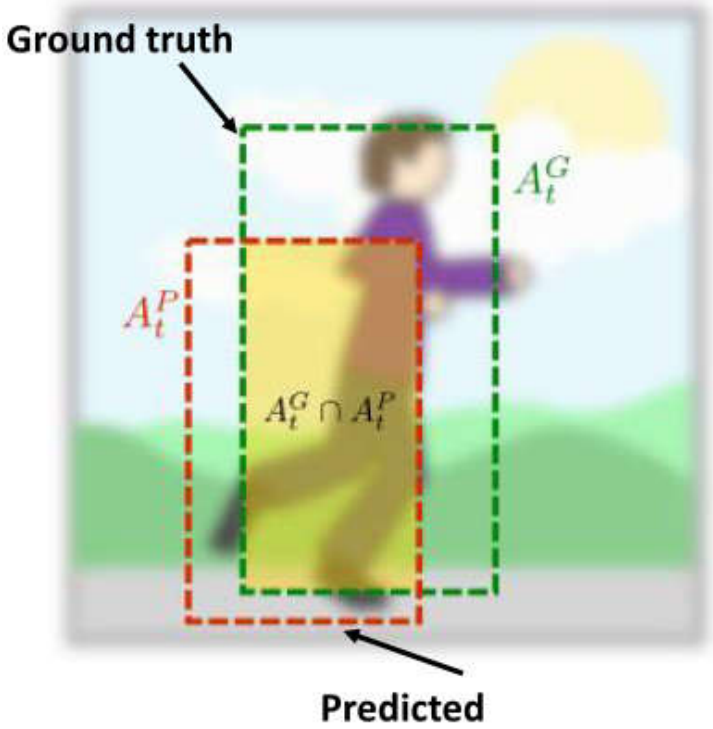
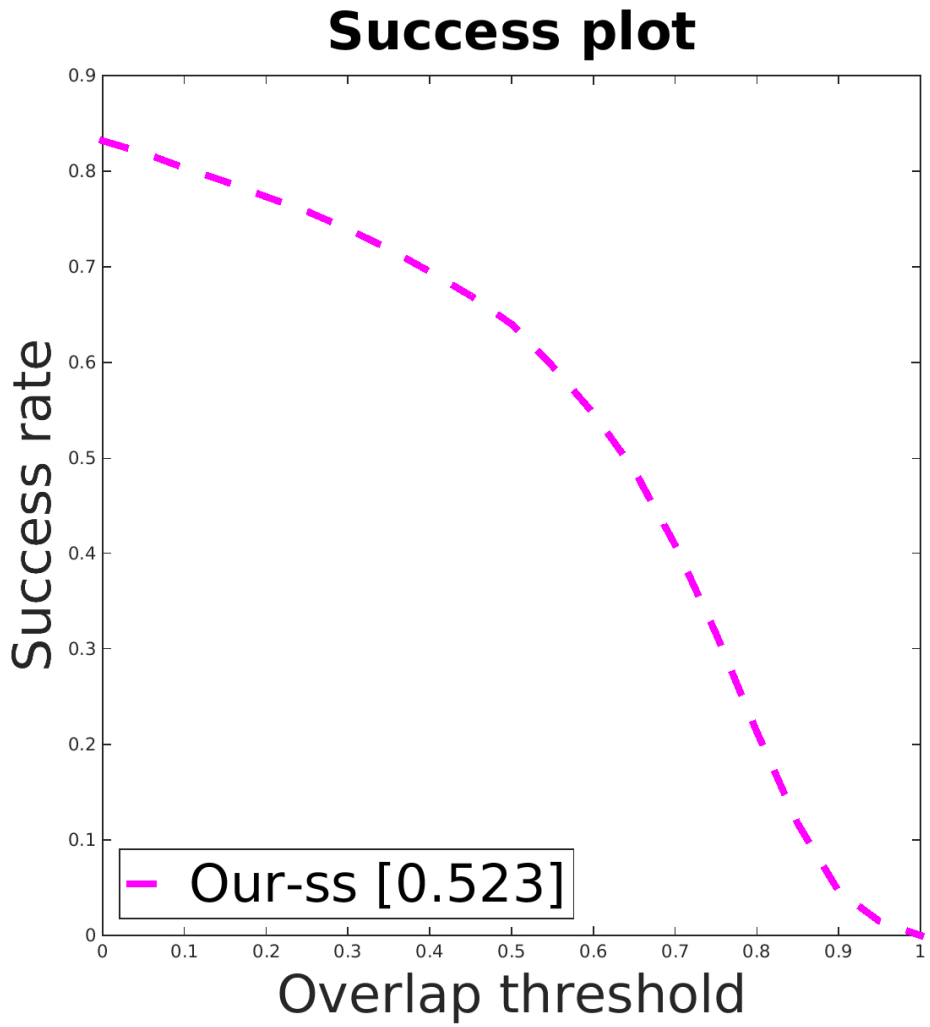


Image courtesy of [Kristan'14]

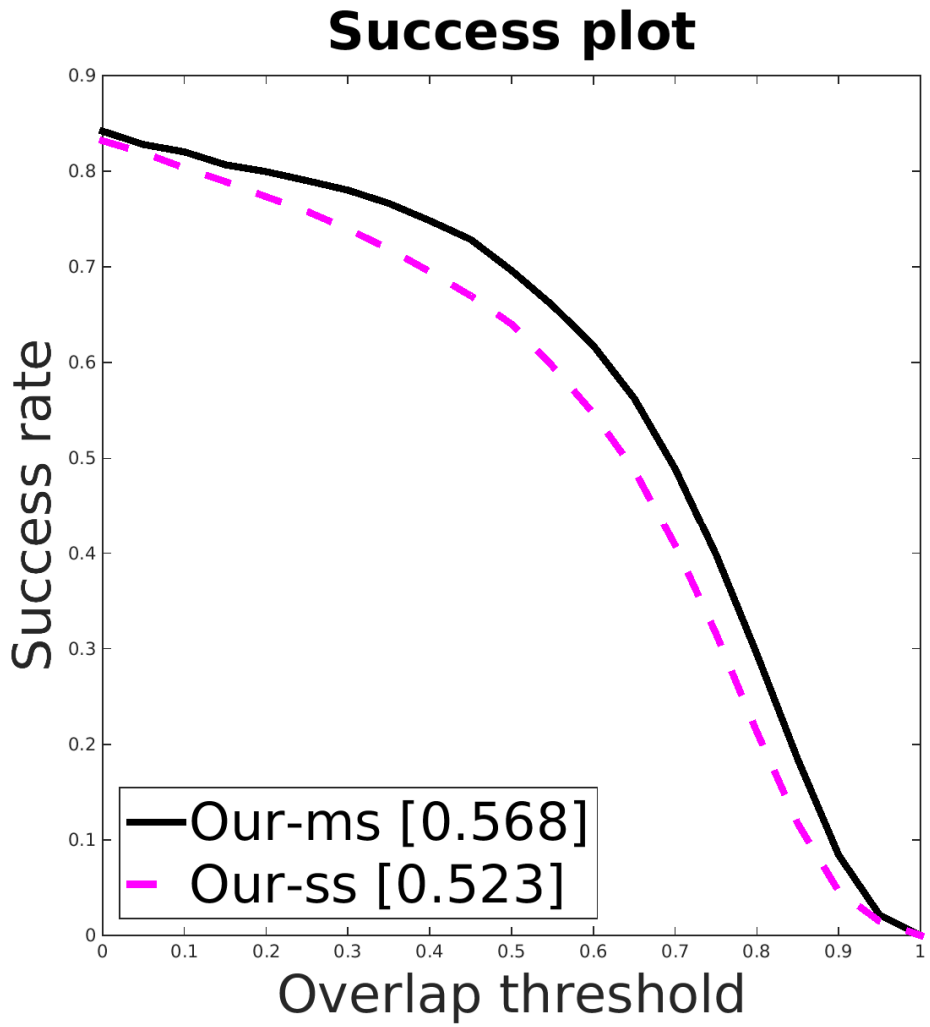
Experimental Results

- Online Tracking Benchmark (OTB) Results: Our variants
  - Our-ss
    - Proposal: detection (single scale)
    - Selection: detection score



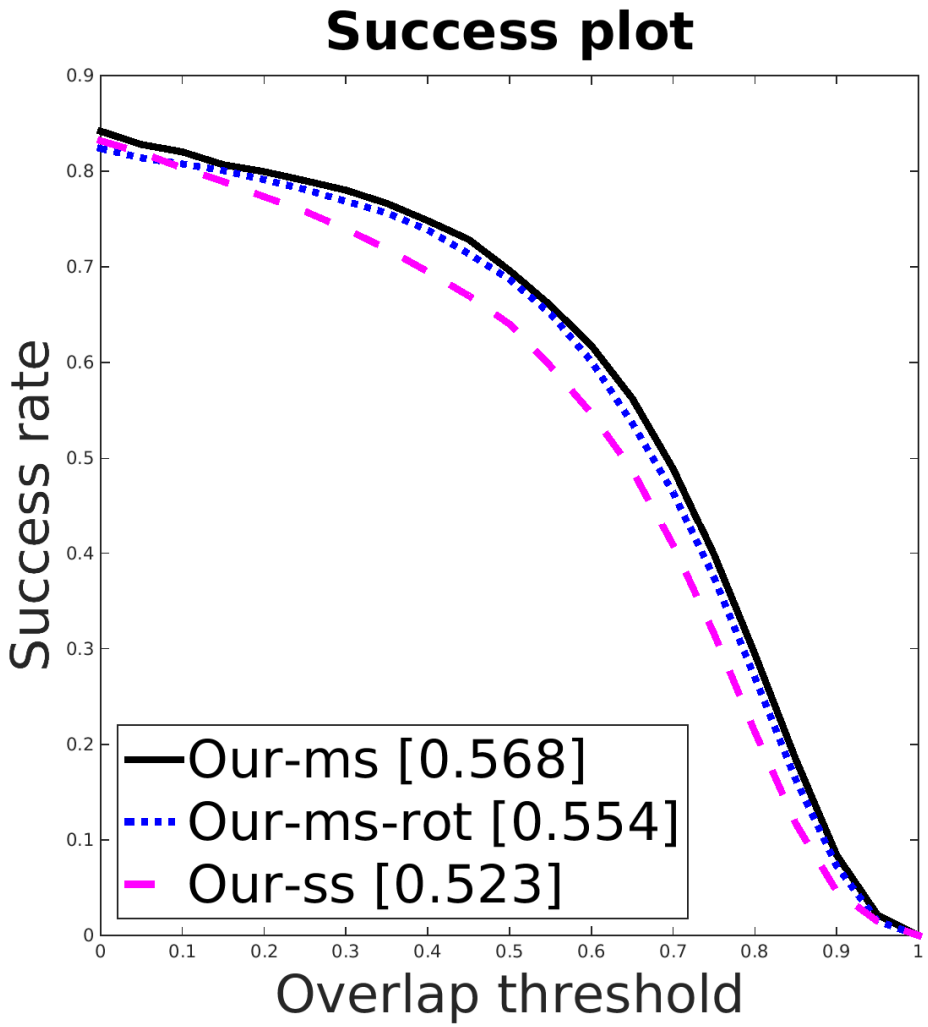
Experimental Results

- Online Tracking Benchmark (OTB) Results: Our variants
  - Our-ms
    - Proposal: detection (multiple scales)
    - Selection: detection score



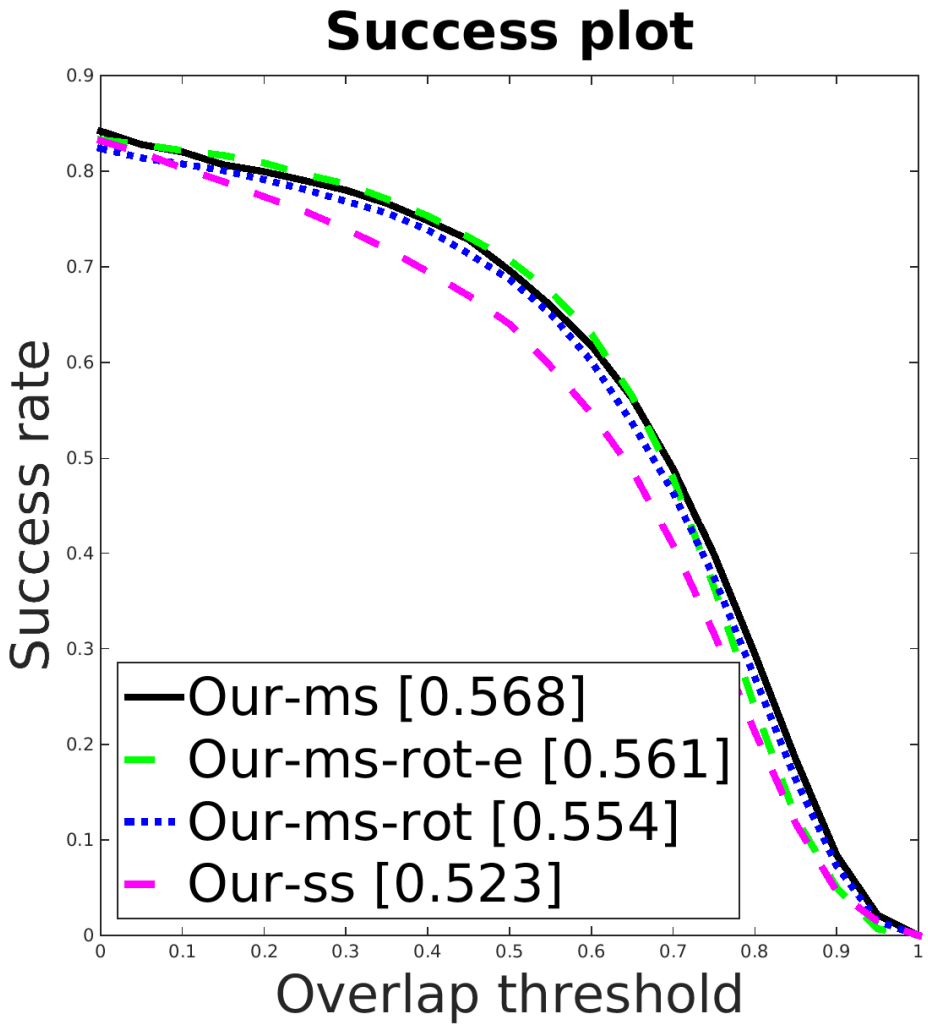
Experimental Results

- Online Tracking Benchmark (OTB) Results: Our variants
  - Our-ms-rot
    - Proposal: detection (multiple scales) + geometry
    - Selection: detection score



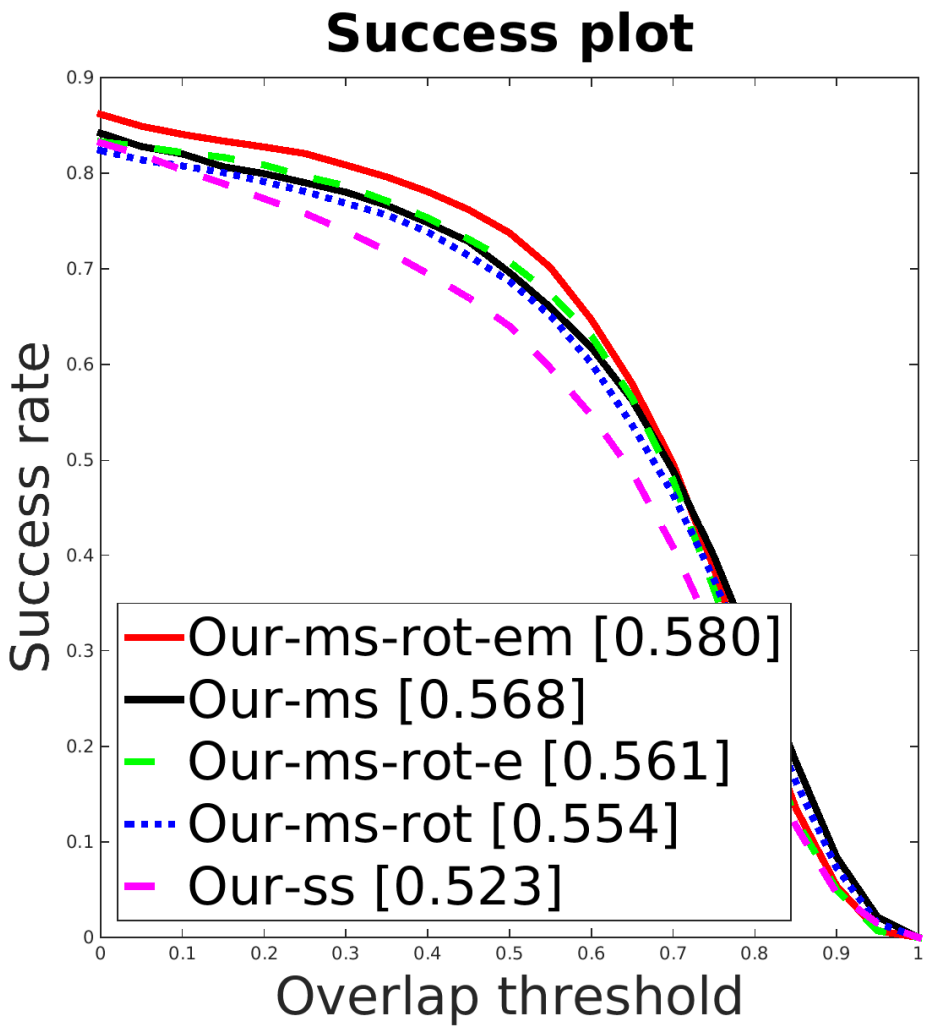
Experimental Results

- Online Tracking Benchmark (OTB) Results: Our variants
  - Our-ms-rot-e
    - Proposal: detection (multiple scales) + geometry
    - Selection: detection + edgebox (edge response) scores



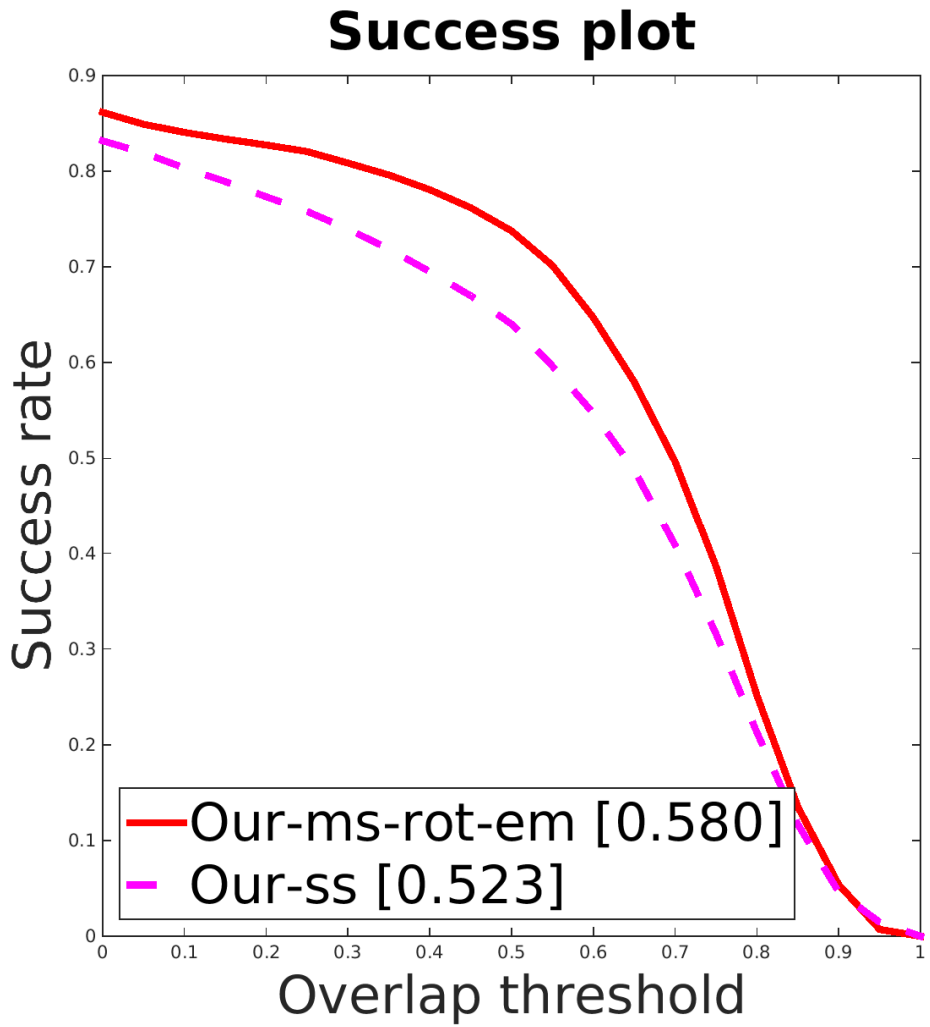
Experimental Results

- Online Tracking Benchmark (OTB) Results: Our variants
  - Our-ms-rot-em
    - Proposal: detection (multiple scales) + geometry
    - Selection: detection + edgebox (edge & motion boundary response) scores



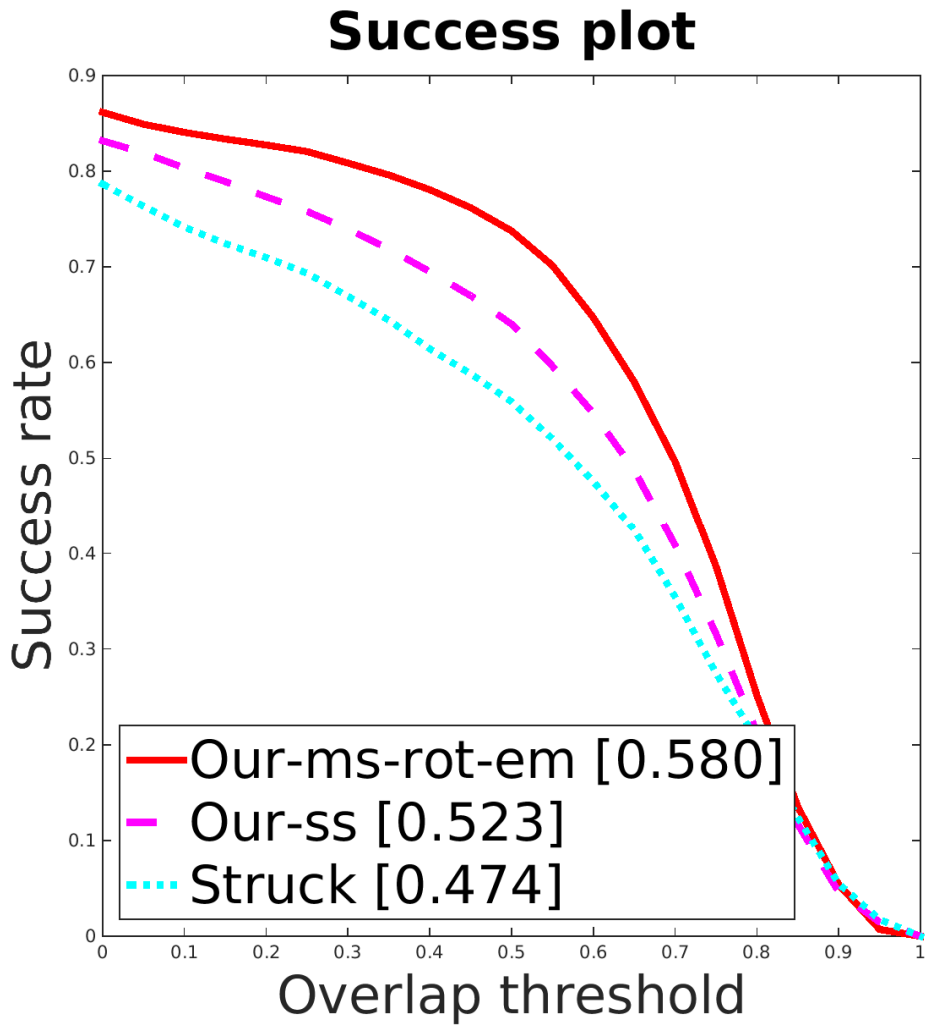
Experimental Results

- Online Tracking Benchmark (OTB) Results: Ours vs. others



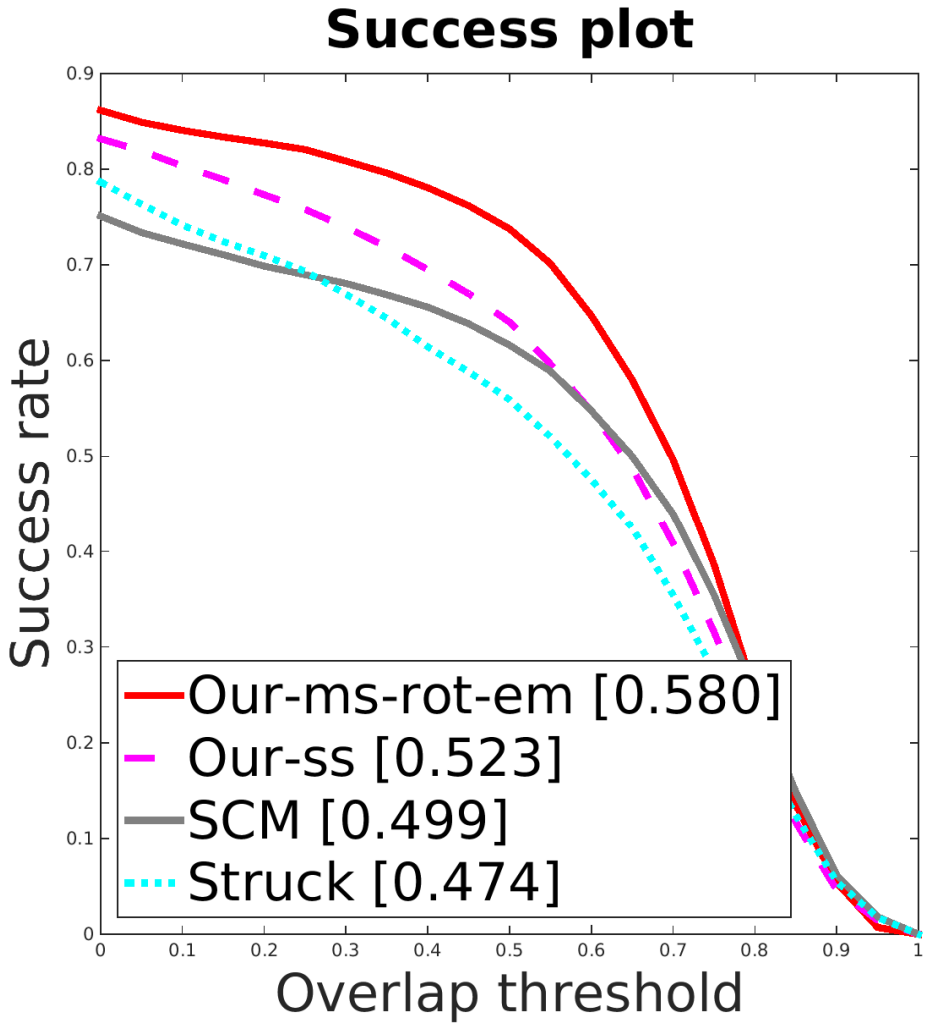
Experimental Results

- Online Tracking Benchmark (OTB) Results: Ours vs. others



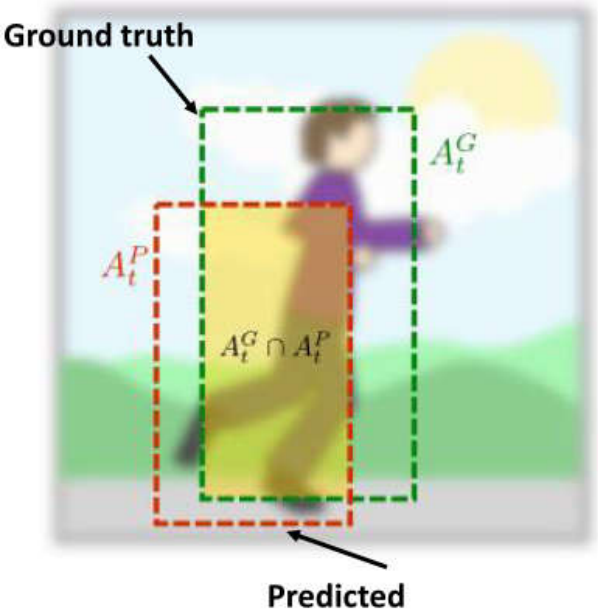
Experimental Results

- Online Tracking Benchmark (OTB) Results: Ours vs. others



Experimental Results

- Participated in VOT 2015 competitions with a **simplified framework**
- Visual Object Tracking (VOT) Challenge Evaluation Metrics
  - Accuracy: Average overlap during successful tracking
  - Robustness: Number of times a tracker drifts off the target



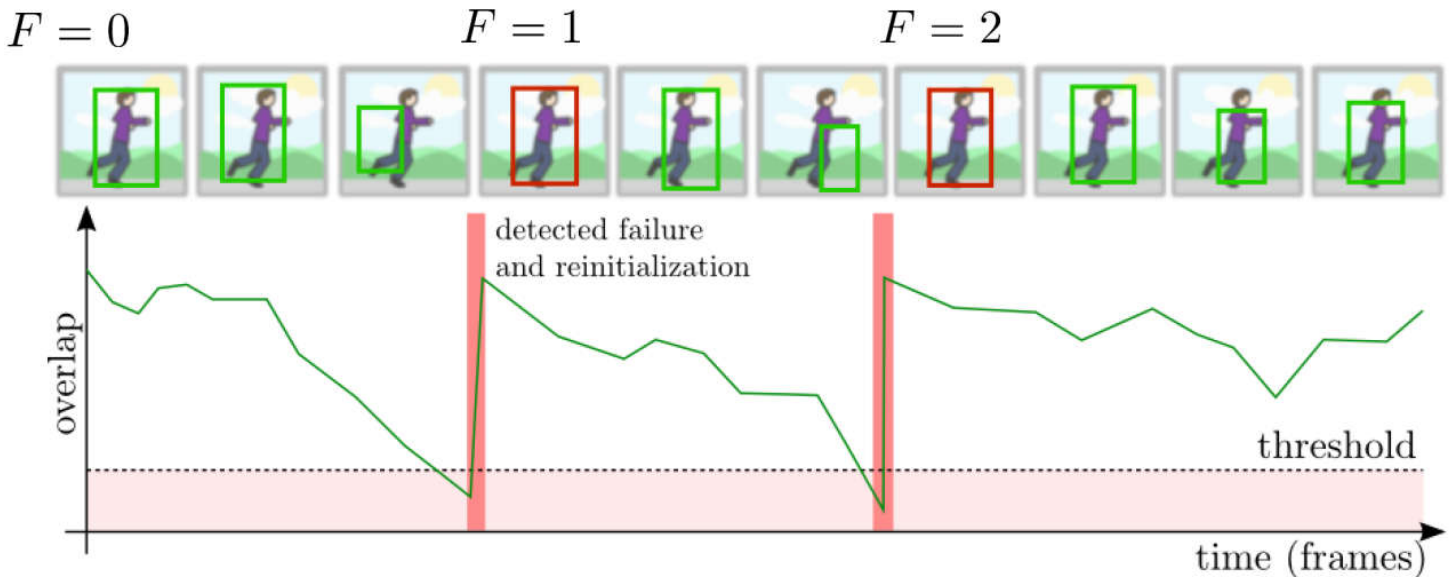
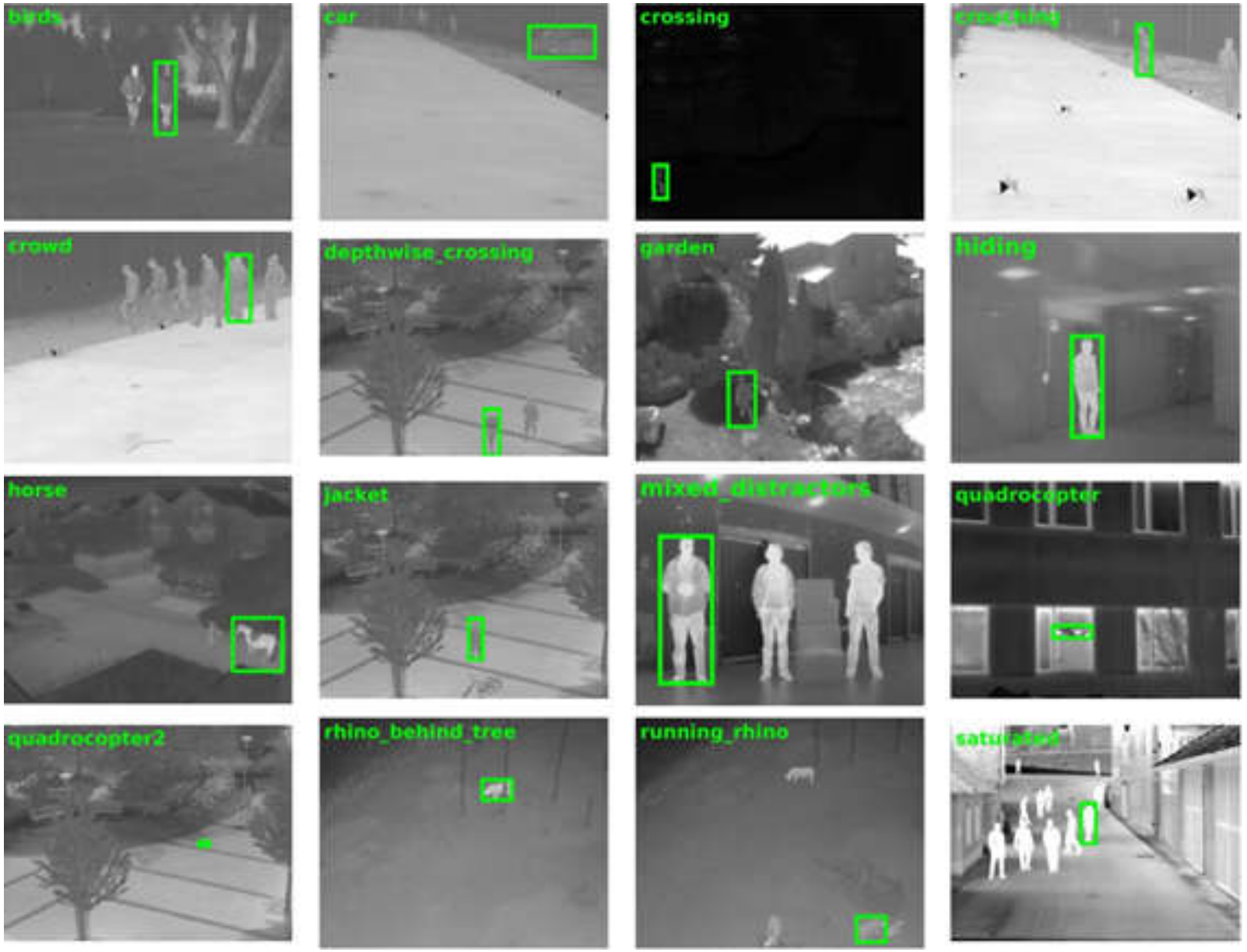


Image courtesy of [Kristan'14]

Experimental Results

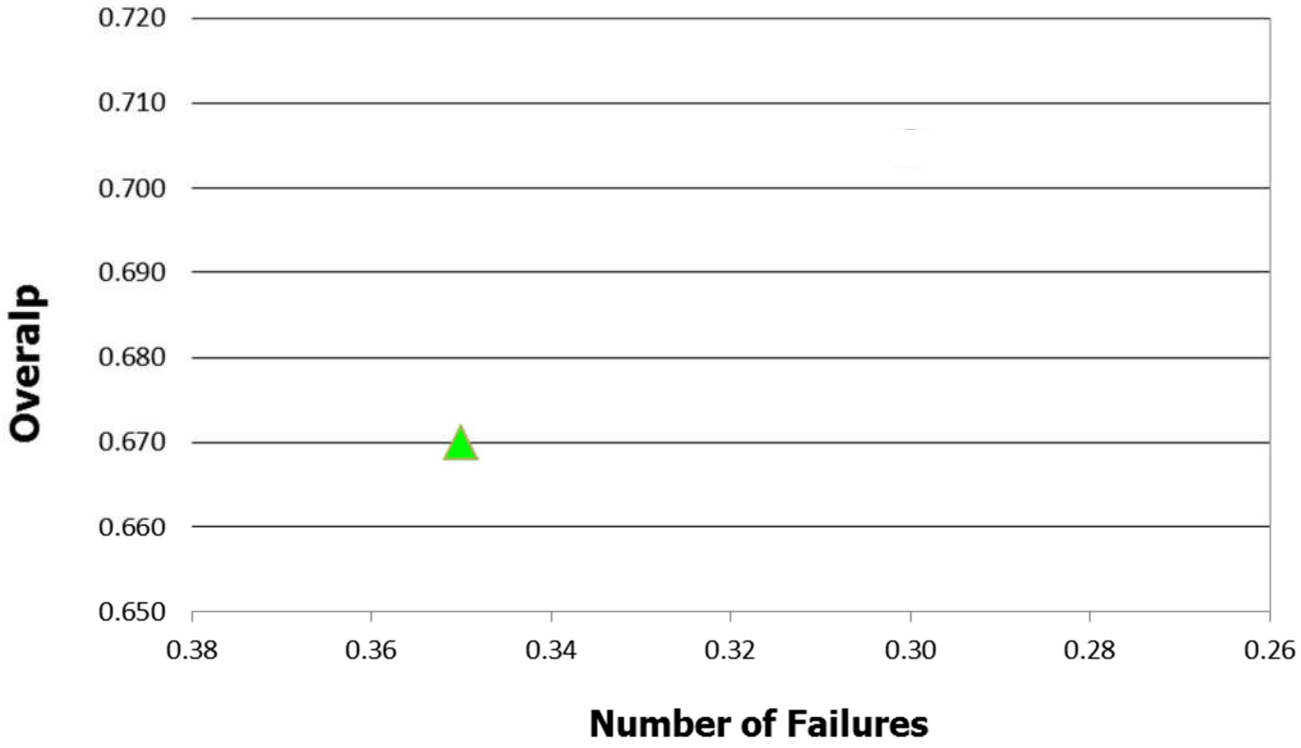
- Thermal Infrared Visual Object Tracking (VOT-TIR) 2015 Challenge Dataset (20 seq.) [Felsberg'15]



Experimental Results

- Thermal Infrared Visual Object Tracking (VOT-TIR) 2015 Challenge Results

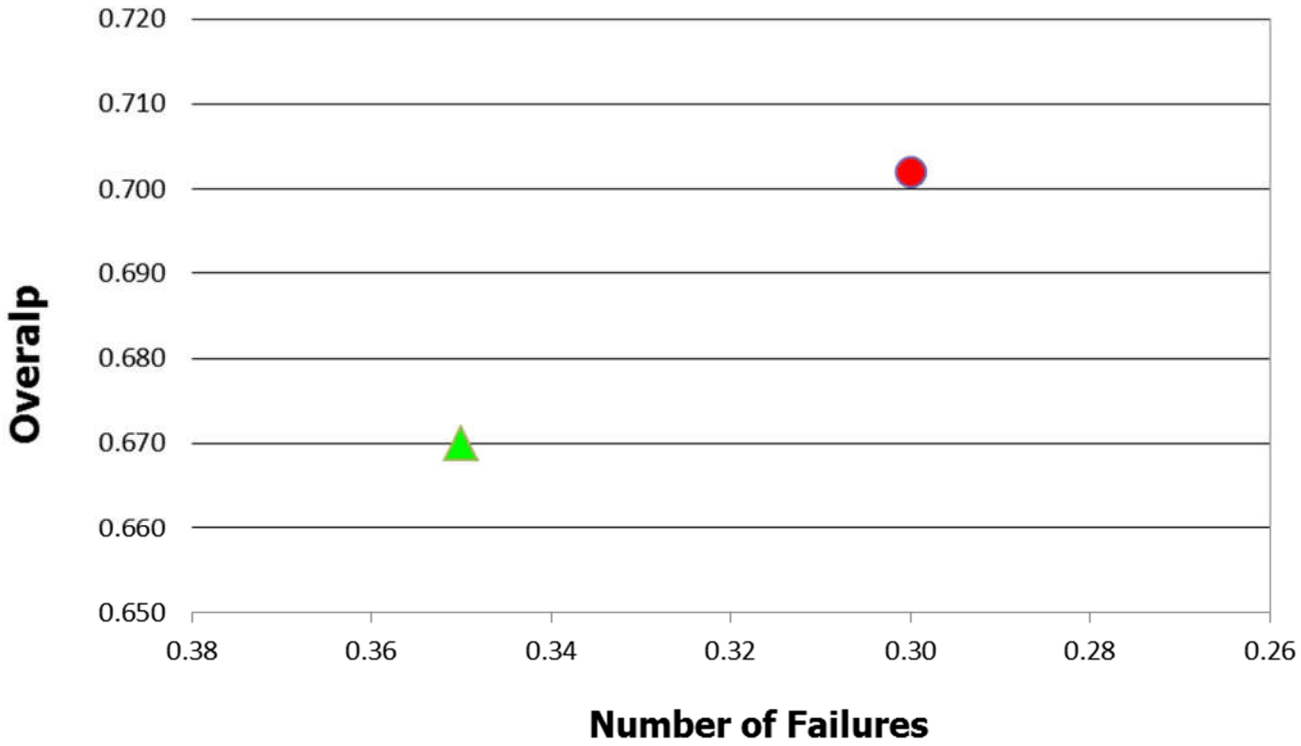
▲ Selection: detection score only	
Acc. (Overlap)	Rob. (#Failures)
0.670	0.35



Experimental Results

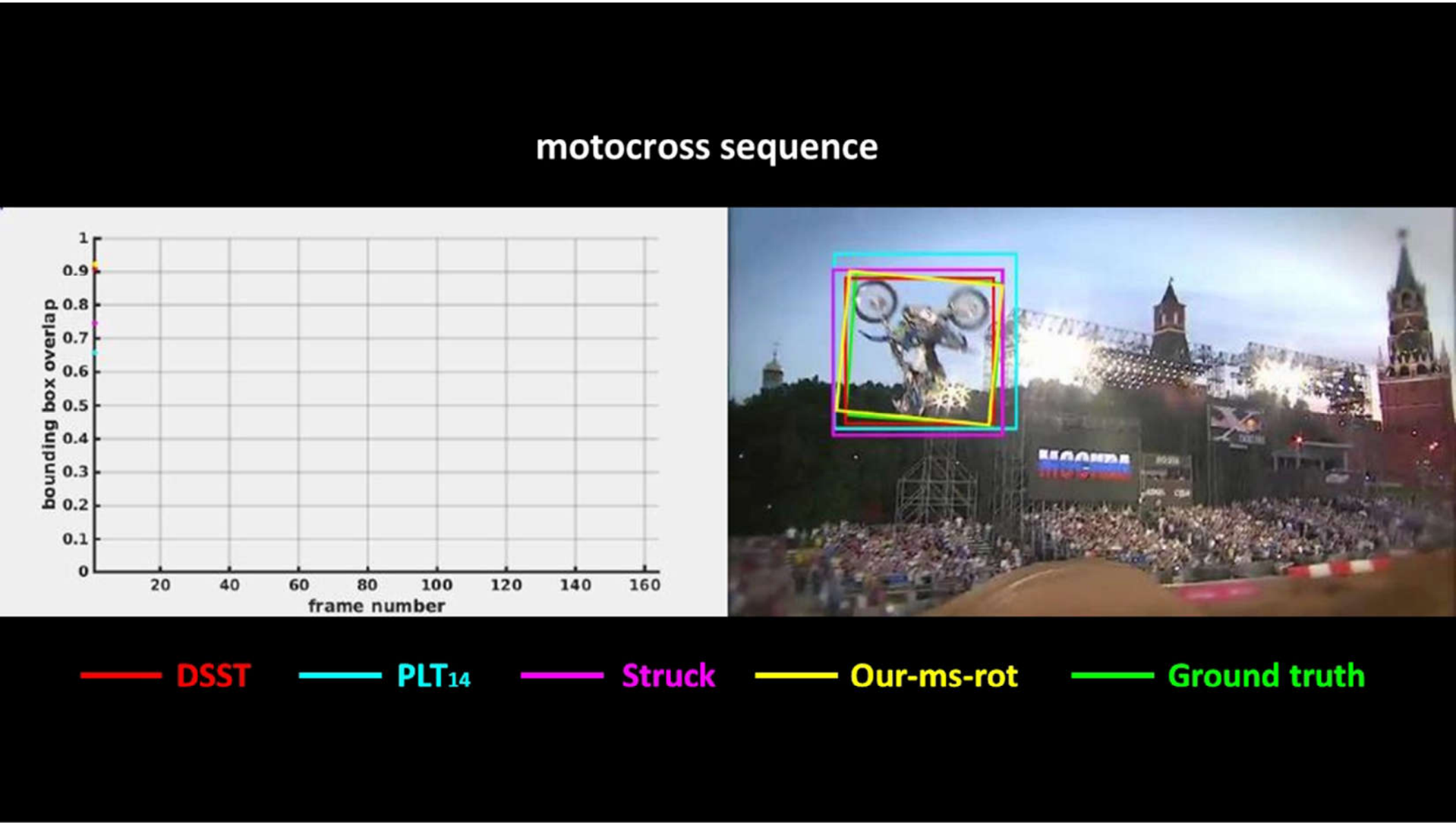
- Thermal Infrared Visual Object Tracking (VOT-TIR) 2015 Challenge Results

▲ Selection: detection score only		● Selection: detection + edgebox score	
Acc. (Overlap)	Rob. (#Failures)	Acc. (Overlap)	Rob. (#Failures)
0.670	0.35	**0.702**	**0.30**



Experimental Results

- Video demo



Summary: Proposal Selection Tracking

- Proposed a generalized discriminative tracking-by-detection framework for short-term tracking
  - New geometry proposals
  - A novel selection scheme based on multiple cues
- Achieved state-of-the-art performance on challenging datasets
- Participated in recent challenges
  - "Winning tracker" from 24 trackers in the VOT-TIR2015
  - Ranked sixth among 62 trackers in the VOT2015

- Publication
  - Y. Hua, K. Alahari, and C. Schmid. Online object tracking with proposal selection. In ICCV, 2015
- Source code released at
  - http://thoth.inrialpes.fr/research/pstracker/

Outline

- Online Object Tracking with Proposal Selection
- ***Occlusion and Motion Reasoning for Long-term Tracking***
- Conclusion and Future Work

Background

- Many tracking methods suffer from the **template update problem** [Matthews'04]
  - To update, or not to update?

Update in every frame

Frame 1 Frame 245 Frame 341 Frame 468

No update

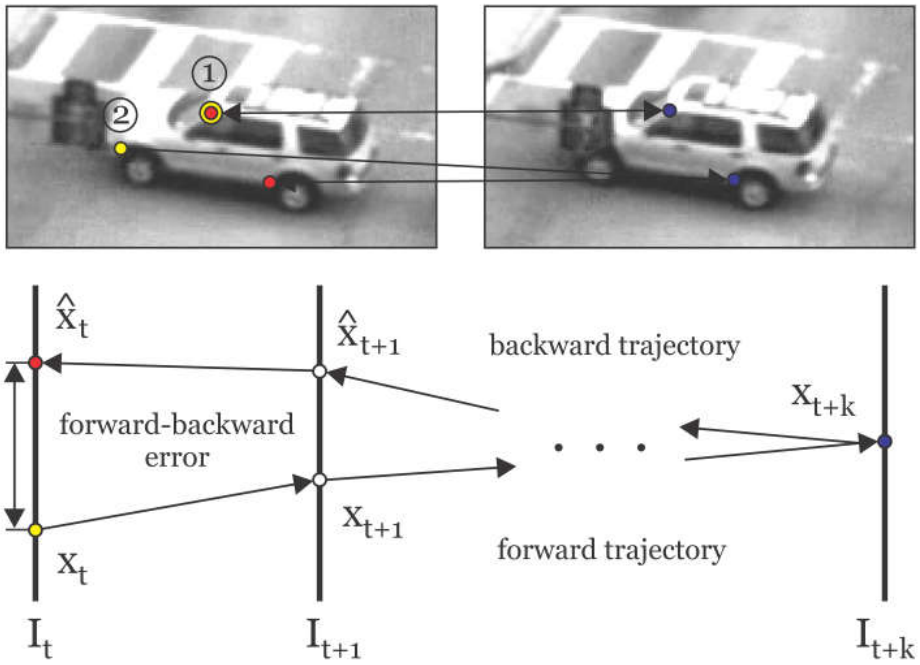
Related Work

- Long-term tracking
  - Investigated in “Tracking-Learning-Detection” [Kalal’12]
  - “… where the object may become **occluded**, significantly change scale, and **leave/re-enter the field-of-view**” [Supancic III’13]

Image courtesy of [Kalal’12]

Related Work

- Key step for long-term tracking: **When to update the model**
  - Forward-backward tracking for checking errors [Kalal'10/12]
  - Self-paced learning for collecting relevant samples [Supancic III'13]



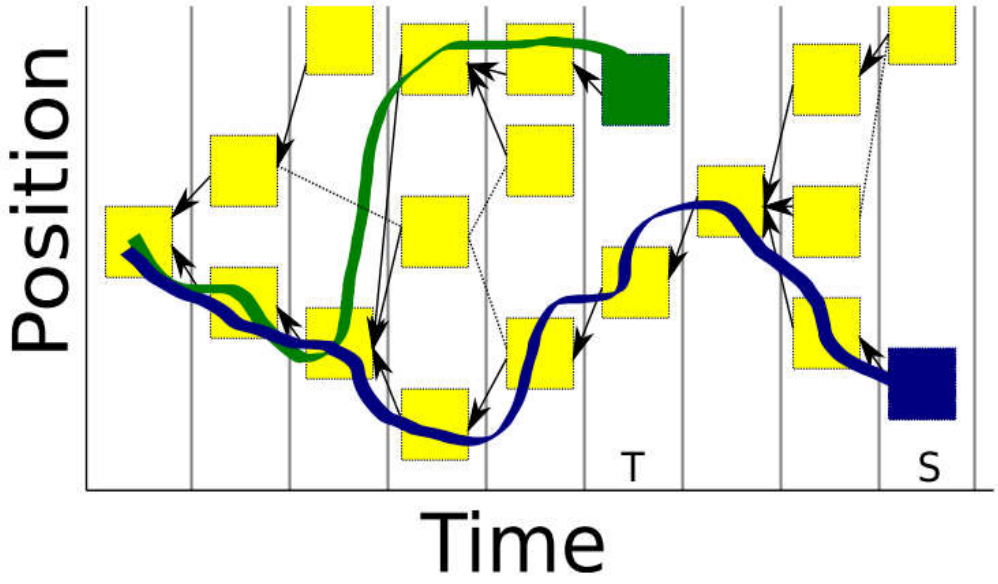
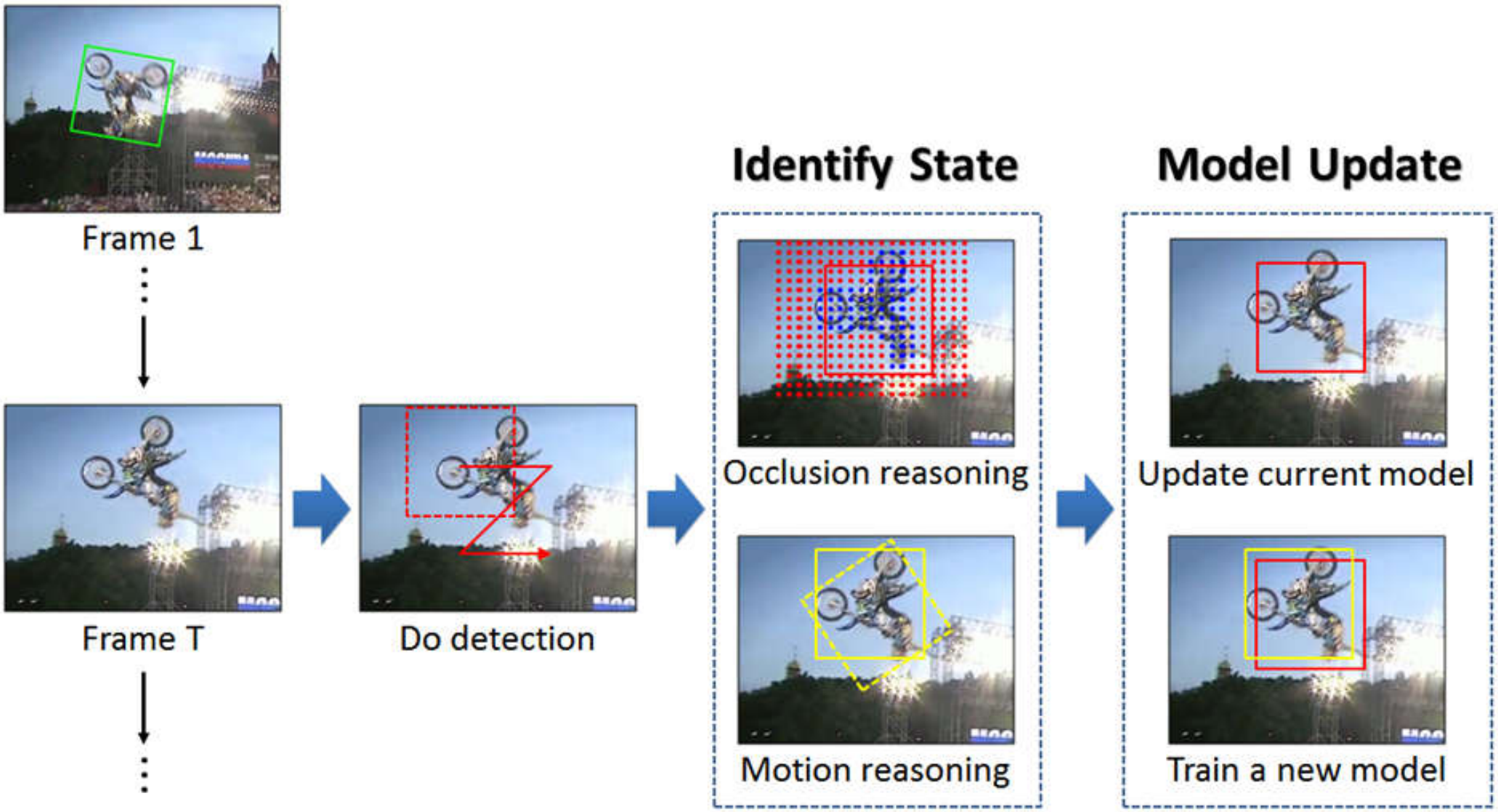


Image courtesy of [Kalal'10, Supancic III'13]

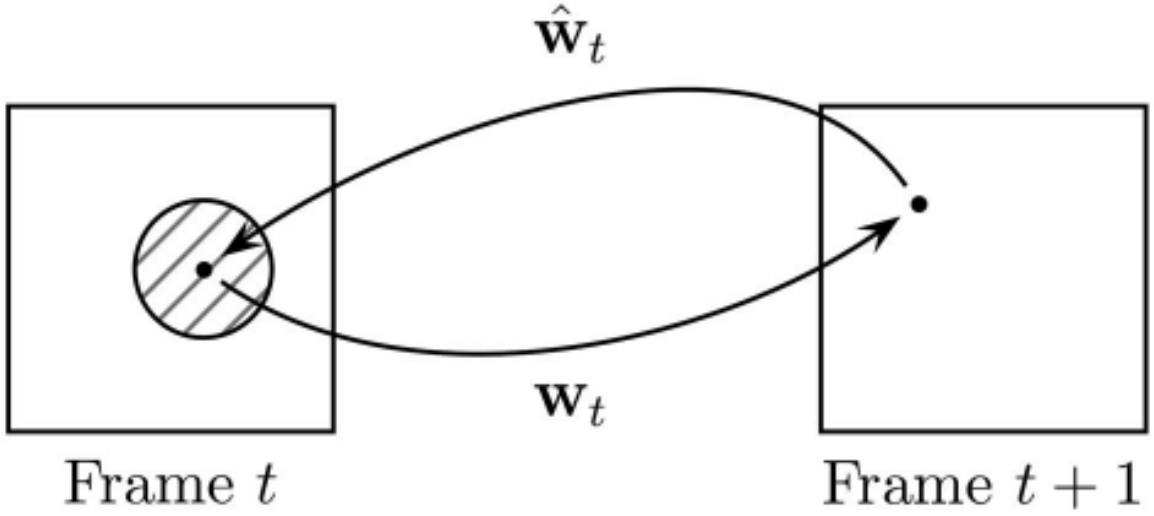
Our approach: Occlusion and Motion Reasoning

Our approach: Occlusion and Motion Reasoning



Motion Cues

- Optical flow
- Long-term tracks [Ochs'14]
  - Built on dense optical flow method [Brox'11]
  - Verification step: consistency of forward and backward flow



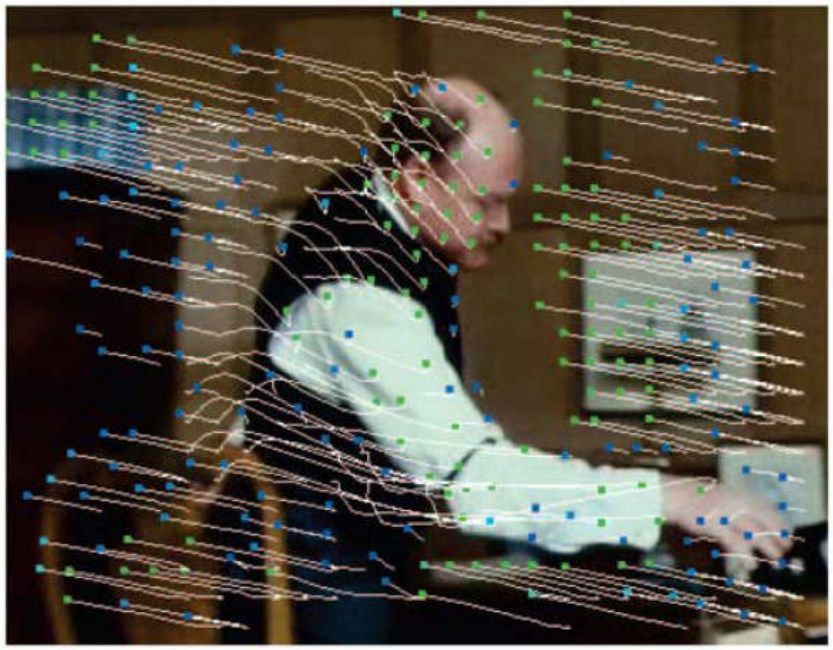
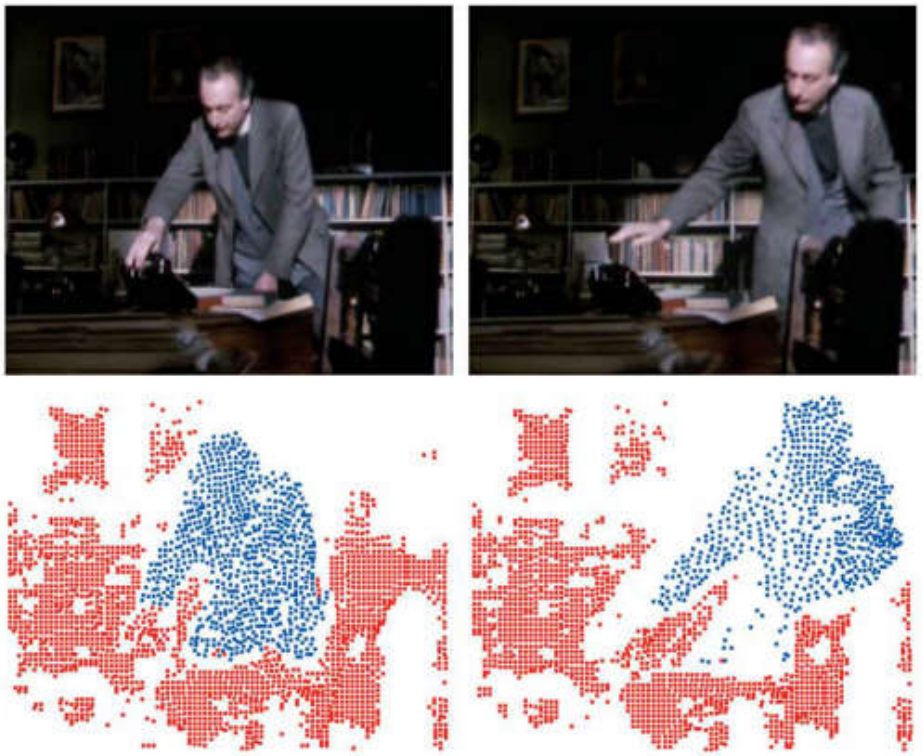


Image courtesy of [Ochs'14]

Motion Cues

- Application
  - Segmentation of Moving Objects by Long Term Video Analysis [Ochs'14]
  - Spatio-temporal Video Segmentation with Long-range Motion Cues [Lezama'11]



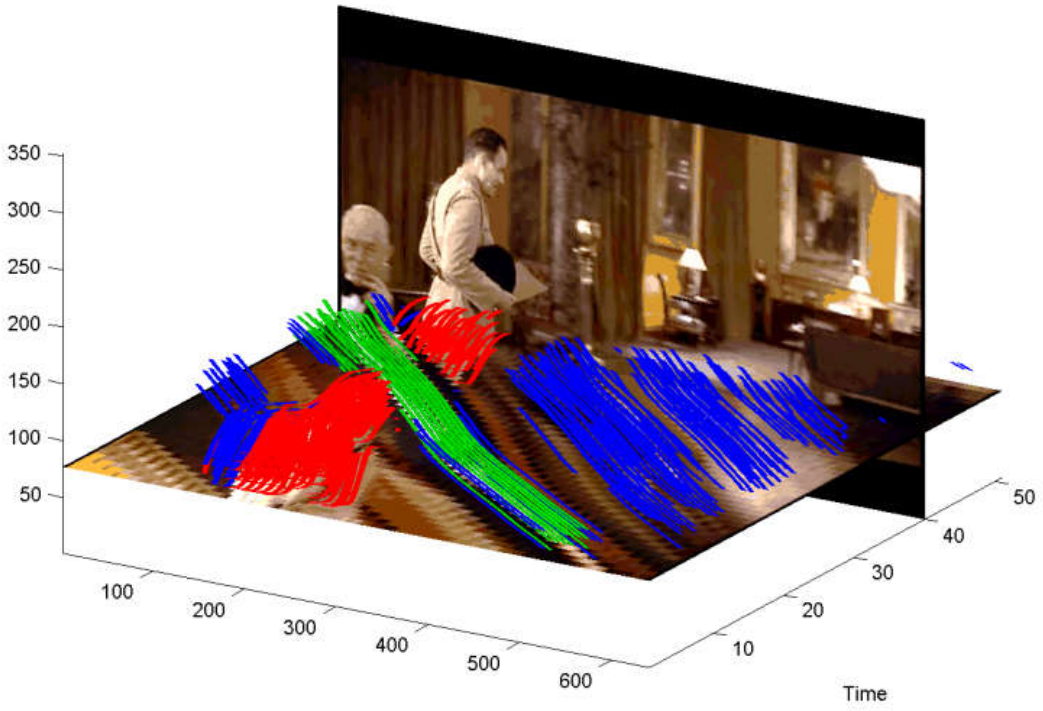


Image courtesy of [Ochs'14, Lezama'11]

Occlusion Reasoning

- Goal: Label long-term tracks as **foreground** or **background**
- Formulation: Energy minimization problem

$$E(x) = \sum_{i=1}^{n} \phi_i(x_i) + \lambda \sum_{(i,j)\in\varepsilon} \phi_{ij}(x_i, x_j)$$

$$where\ \phi_i(x_i = 1) = \begin{cases} 1 - \dfrac{1}{1 + \exp(\alpha * d_t + \beta)} & if\ track_i \in box_t \\ 0.5 & otherwise \end{cases}$$

detection score of box_t

Occlusion Reasoning

- Goal: Label long-term tracks as **foreground** or **background**
- Formulation: Energy minimization problem

$$E(x) = \sum_{i=1}^{n} \phi_i(x_i) + \lambda \sum_{(i,j)\in\varepsilon} \phi_{ij}(x_i, x_j)$$

$$where\ \phi_{ij}(x_i, x_j) = \begin{cases} \exp\left(-\lambda_d d(i,j)\right) & if\ x_i \neq x_j \\ 0 & otherwise \end{cases}$$

pointwise distance between tracks

Occlusion Reasoning

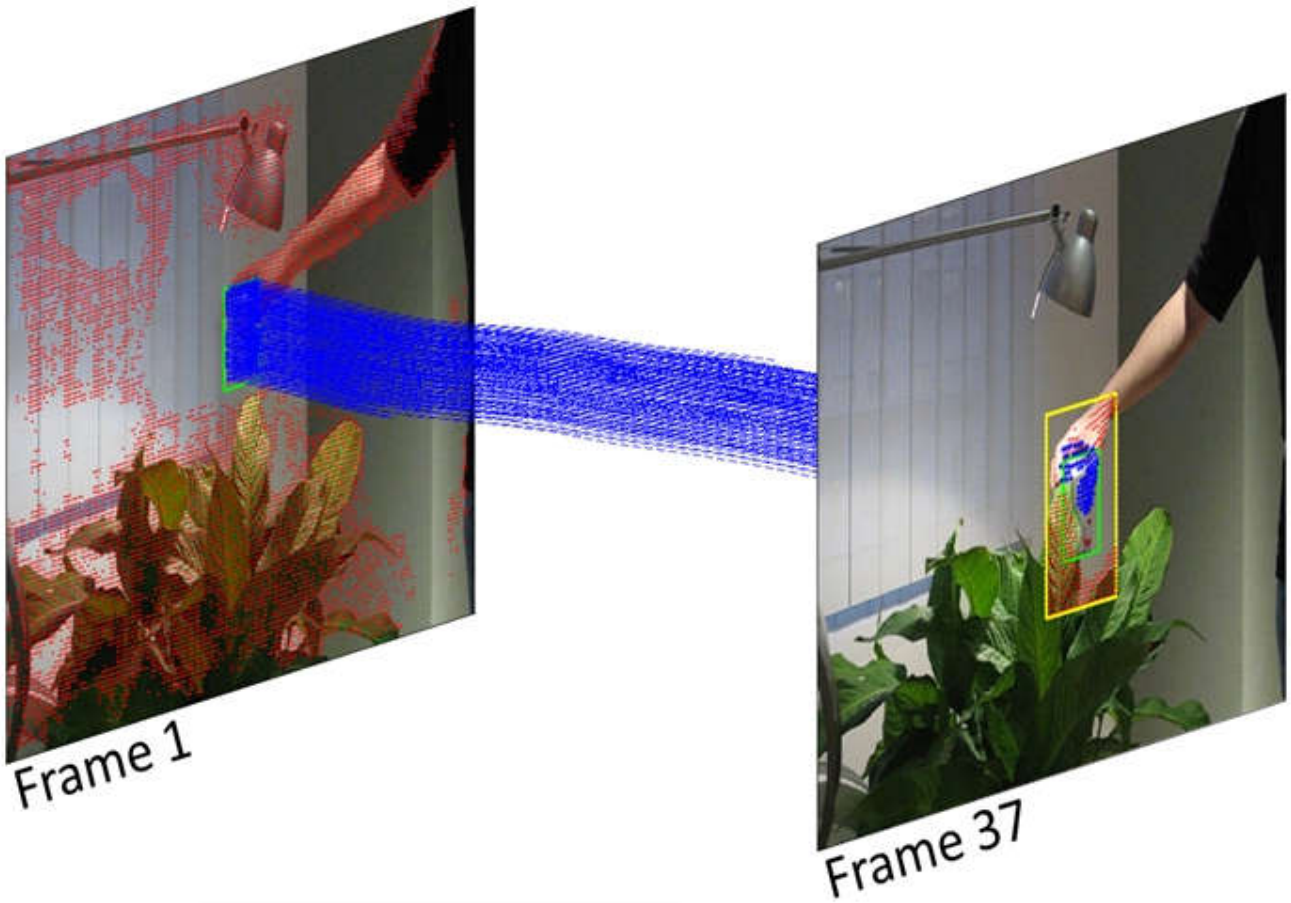
- Goal: Label long-term tracks as **foreground** or **background**
- Formulation: Energy minimization problem

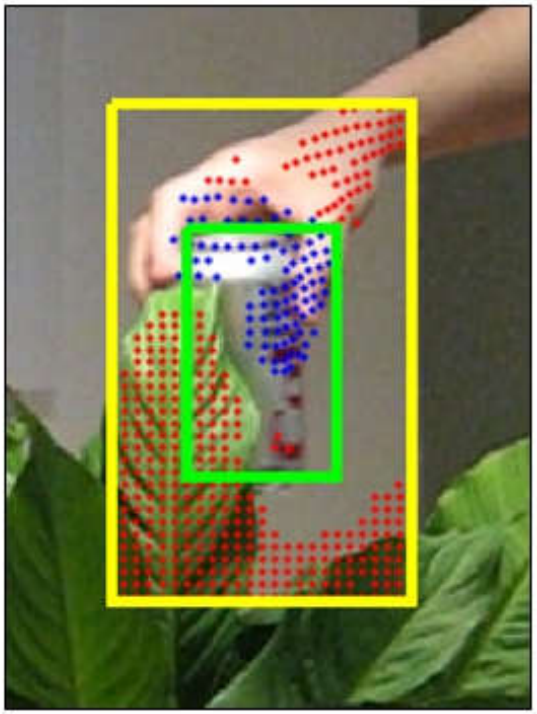
$$E(x) = \sum_{i=1}^{n} \phi_i(x_i) + \lambda \sum_{(i,j)\in\varepsilon} \phi_{ij}(x_i, x_j)$$

- Solver: Graph cuts algorithm [Kolmogorov'04]

Occlusion Reasoning

- Occlusion state estimation via long-term tracks

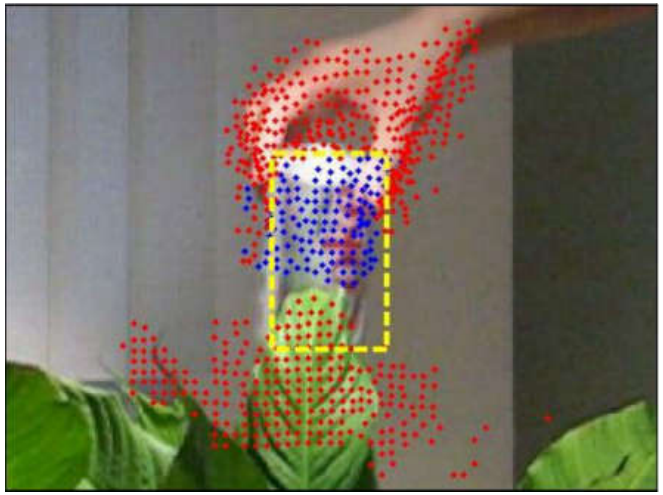




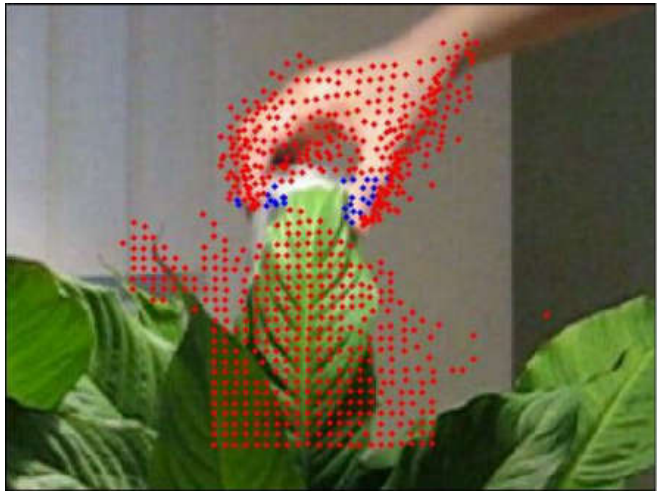
Track labels

Occlusion Reasoning

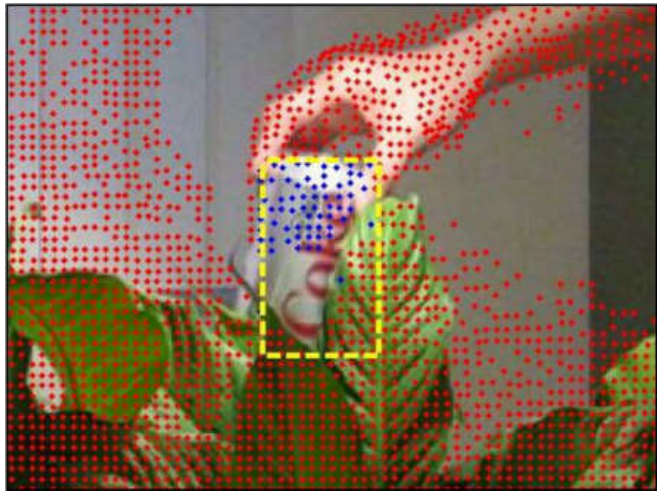
- Selectively update model according to the state of the object



Frame 251: Partial occlusion
Continue to track and no model updating



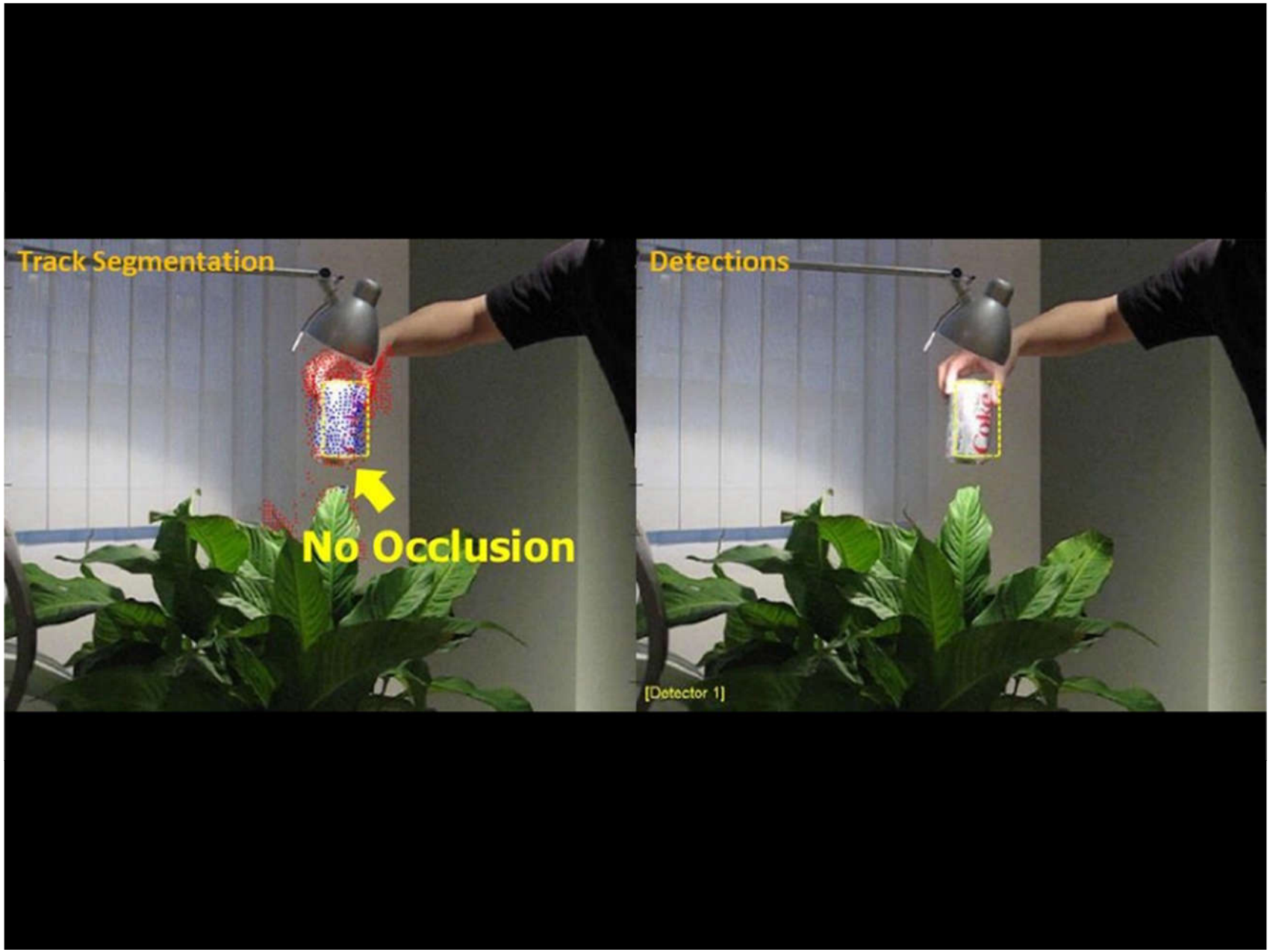
Frame 254: Full occlusion
Stop tracking and no model updating



Frame 269: Object reappears
Recover from occlusion by scanning detector globally

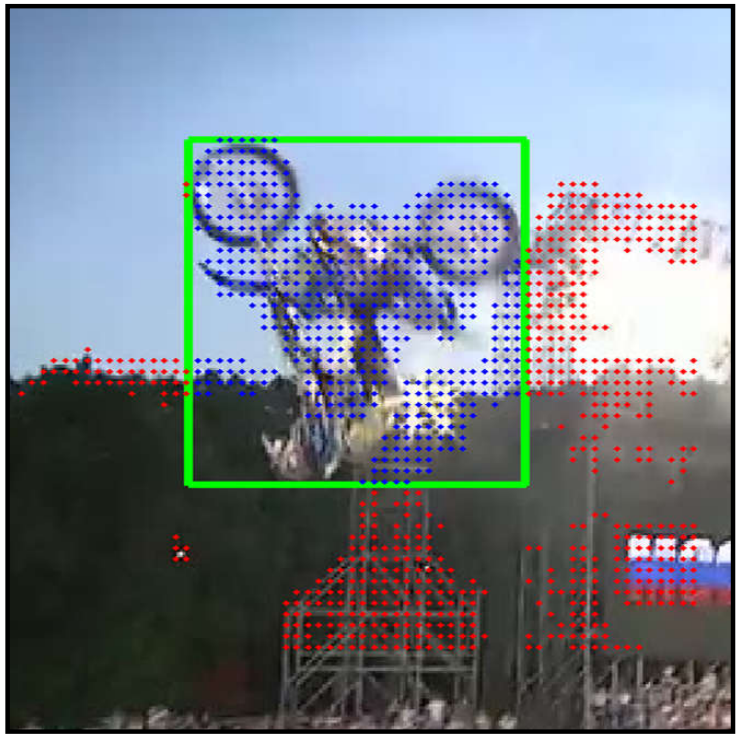
Occlusion Reasoning

- Video demo

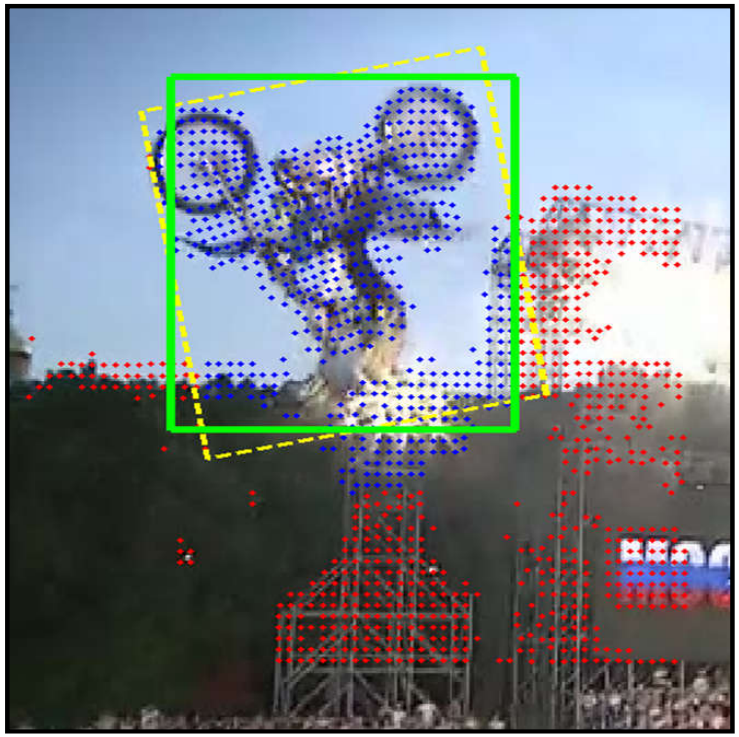


Motion Reasoning

- Estimate accumulated similarity transformations over frames
- Add a new detector if a significant change occurs



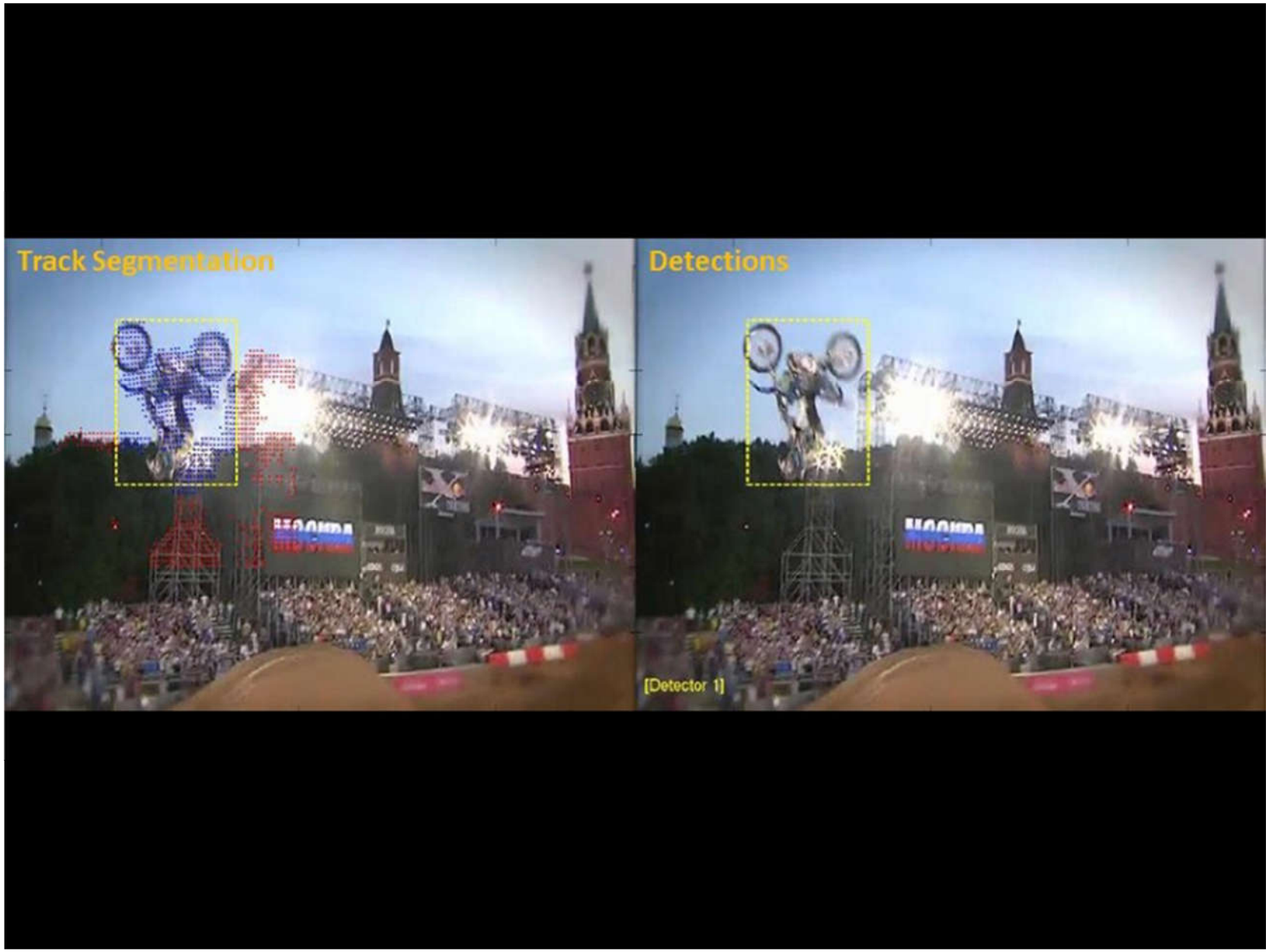
Frame 1



Frame 4

Motion Reasoning

- Video demo



Experimental Results

- Evaluation metrics [Kalal'12]
  - $F_1\ score = 2\ * precision * recall\ /\ (precision + recall)$
  - The threshold of overlap is set to 0.5

- Methods for comparison
  - Struck: Structured Output Tracking with Kernels (Struck) [Hare'11]
  - Tracking-Learning-Detection (TLD) [Kalal'12]
  - Self-paced learning for long-term tracking (SPLTT) [Supancic III'13]

Experimental Results

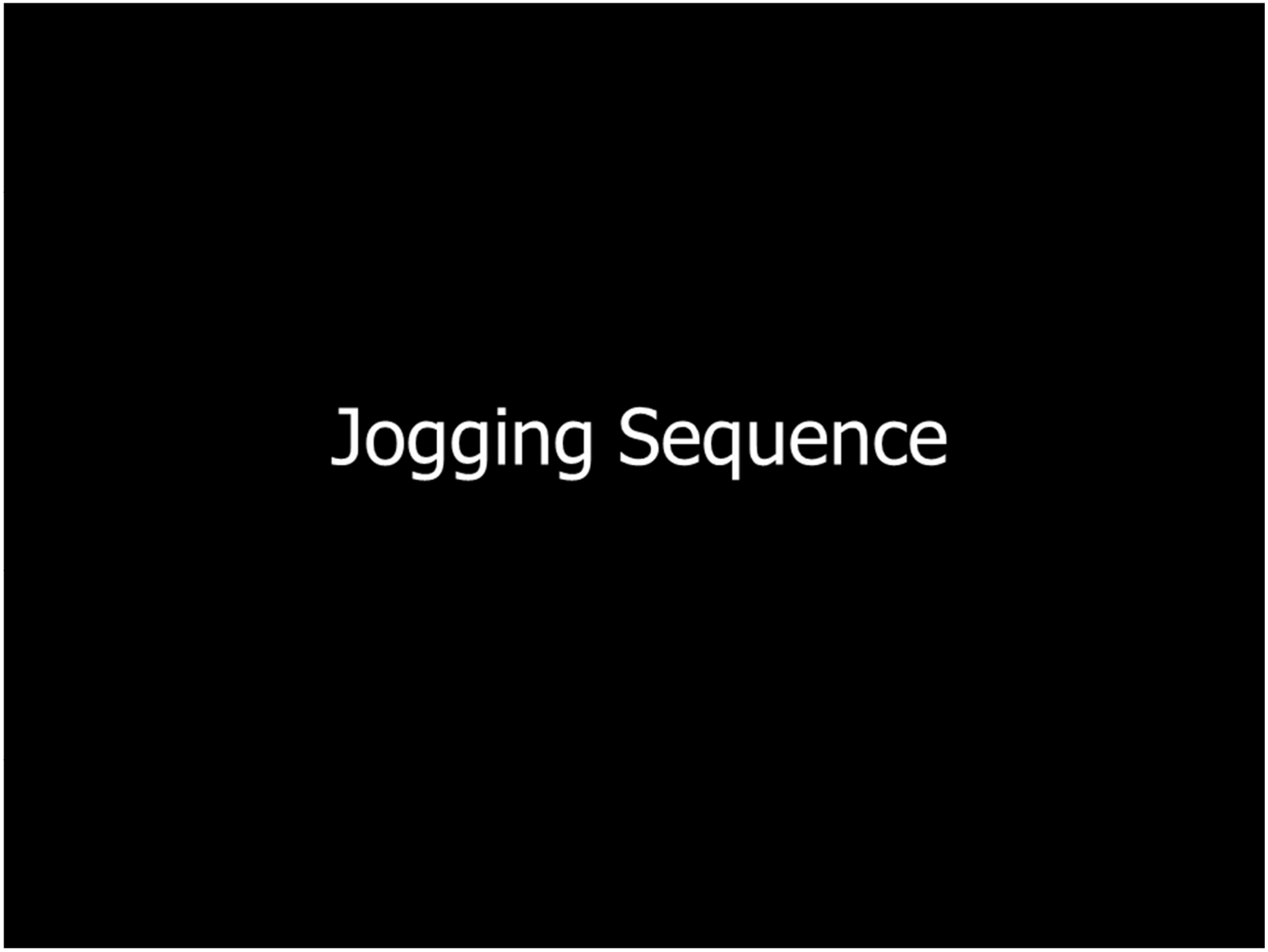
- Online Tracking Benchmark (OTB) Dataset (50 seq.) [Wu'13]
  - Overall results on 50 sequences comparing with other methods

	Struck	TLD	SPLTT	Ours
F_1 score	0.565	0.513	0.661	0.657

  - The results comparable to our ICCV 2015 tracker
    - i.e., Proposal Selection Tracker – Single Scale (PST-ss)
    - However, significantly better on sequences with occlusion

Experimental Results

- Online Tracking Benchmark (OTB) Dataset (50 seq.) [Wu'13]
  - Video demo

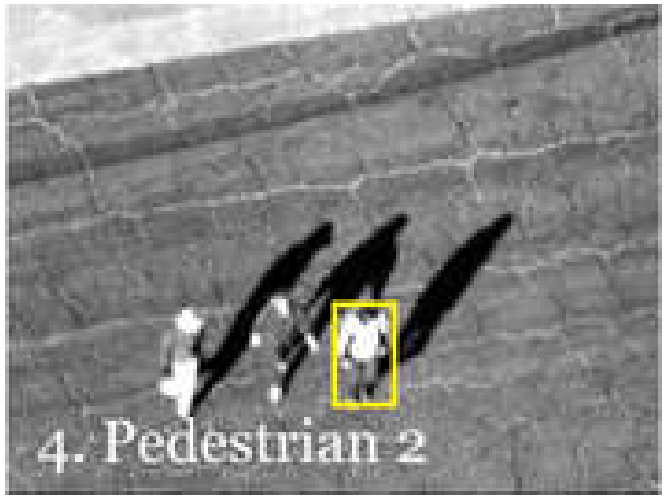


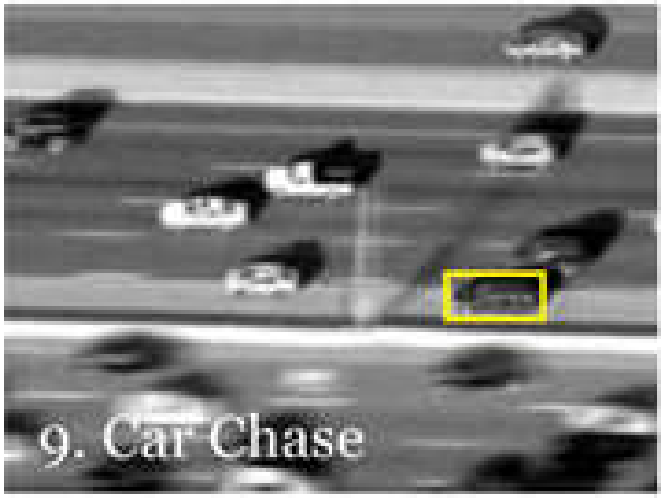
Experimental Results

- Online Tracking Benchmark (OTB) Dataset [Wu'13]
  - Ambiguity of ground truth annotation

Experimental Results

- Tracking-Learning-Detection (TLD) Dataset (3 seq.) [Kalal'12]



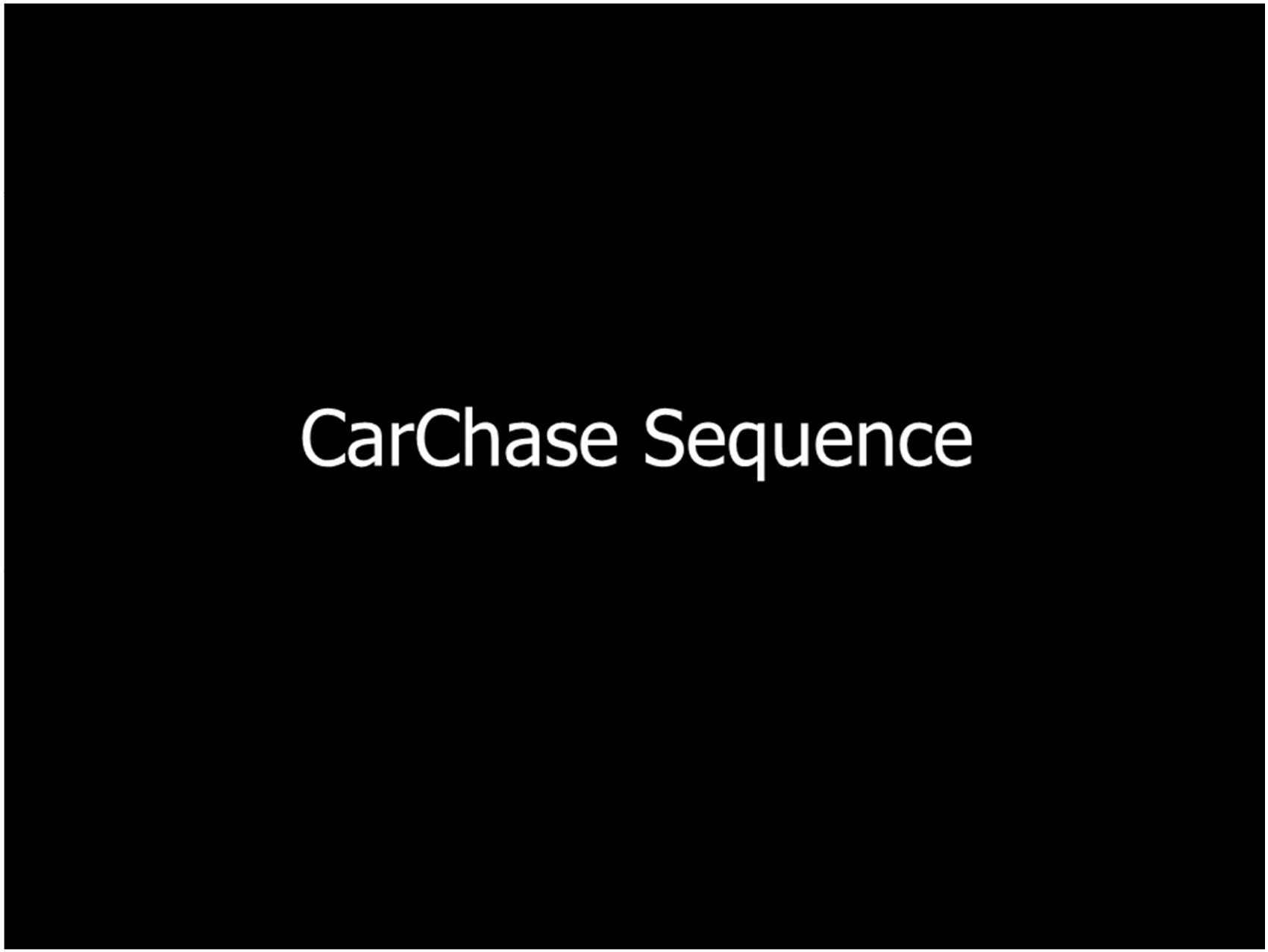


- Results on three long-term sequences

	Struck	TLD	SPLTT	Ours
Pedestrian 2	0.175	0.500	0.950	**0.979**
Pedestrian 3	0.353	0.886	0.989	**1.000**
Car Chase	0.036	**0.340**	0.290	0.312

Experimental Results

- Video demo



Summary: Occlusion and Motion Reasoning

- Proposed a principled way to identify the state of the object based on motion cues
  - Identify occlusion state via long-term track segmentation
  - Estimate change-in-viewpoint with geometric transformations
- Addressed model update problem for long-term tracking
  - Selectively update/create the object model based on the state of the object

- Publication
  - Y. Hua, K. Alahari, and C. Schmid. Occlusion and motion reasoning for long-term tracking. In ECCV, 2014

Outline

- Online Object Tracking with Proposal Selection
- Occlusion and Motion Reasoning for Long-term Tracking
- ***Conclusion and Future Work***

Conclusion

- Online Object Tracking with Proposal Selection
  - Proposed a generalized discriminative tracking-by-detection framework for short-term tracking
  - Achieved state-of-the-art performance on challenging datasets
- Occlusion and Motion Reasoning for Long-term Tracking
  - Proposed a principled way to identify the state of the object using motion cues
  - Addressed the model update problem for long-term tracking

- Publications & Award
  - Y. Hua, K. Alahari, and C. Schmid. Occlusion and motion reasoning for long-term tracking. In ECCV, 2014
  - Y. Hua, K. Alahari, and C. Schmid. Online object tracking with proposal selection. In ICCV, 2015
  - “Winning tracker” in the VOT-TIR2015 challenge

Future Work: Proposal Selection Tracking

- Handle deformable objects
  - Propose more candidates from
    - General object proposals [Zhu'15, Ren'15]
    - Deformable object trackers [Godec'11, Liu '15]

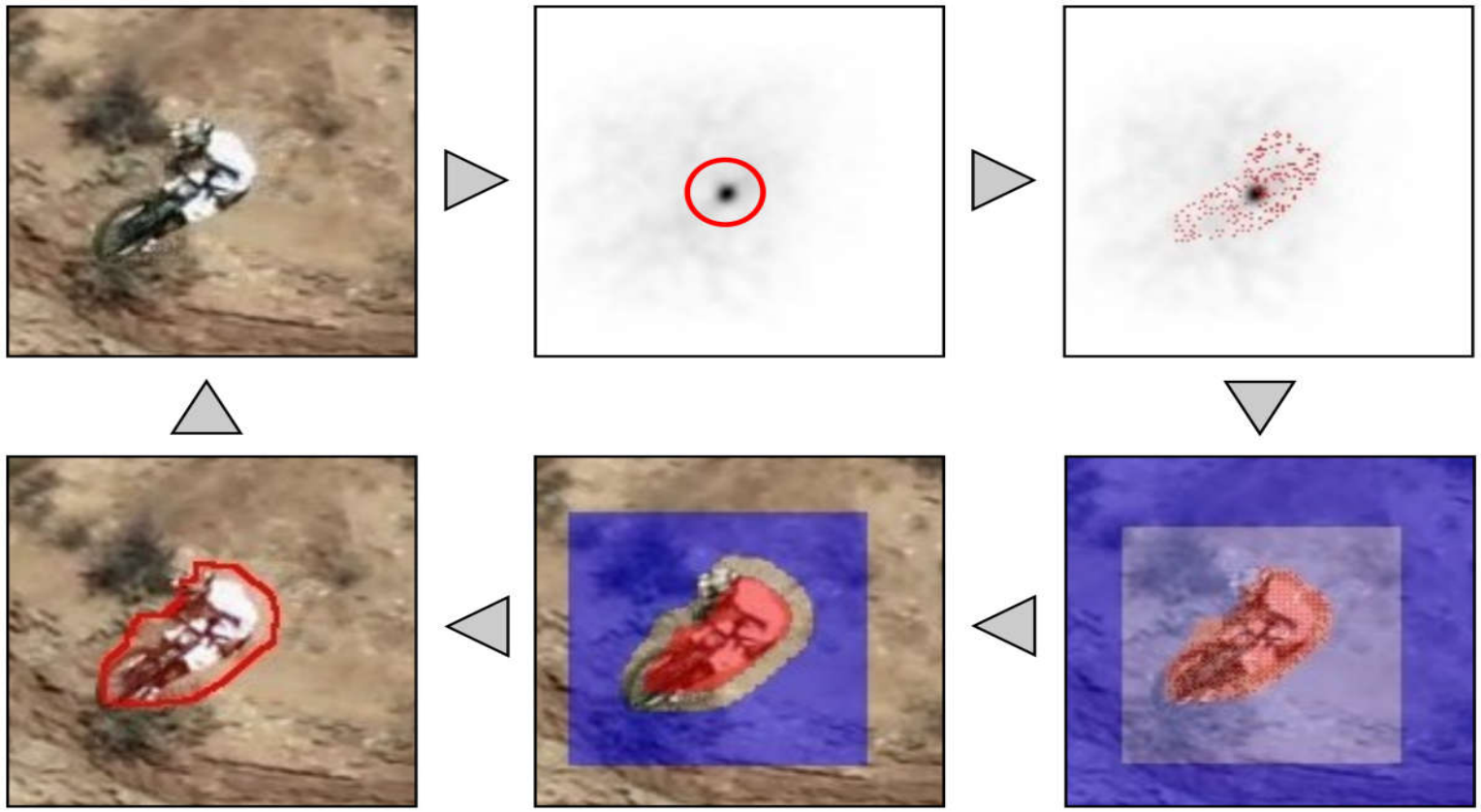


Image courtesy of [Godec'11]

Future Work: Proposal Selection Tracking

- Handle deformable objects
  - Propose more candidates from
    - General object proposals [Zhu'15, Ren'15]
    - Deformable object trackers [Godec'11, Liu '15]
    - Object segmentation [Li'13, Wen'15]

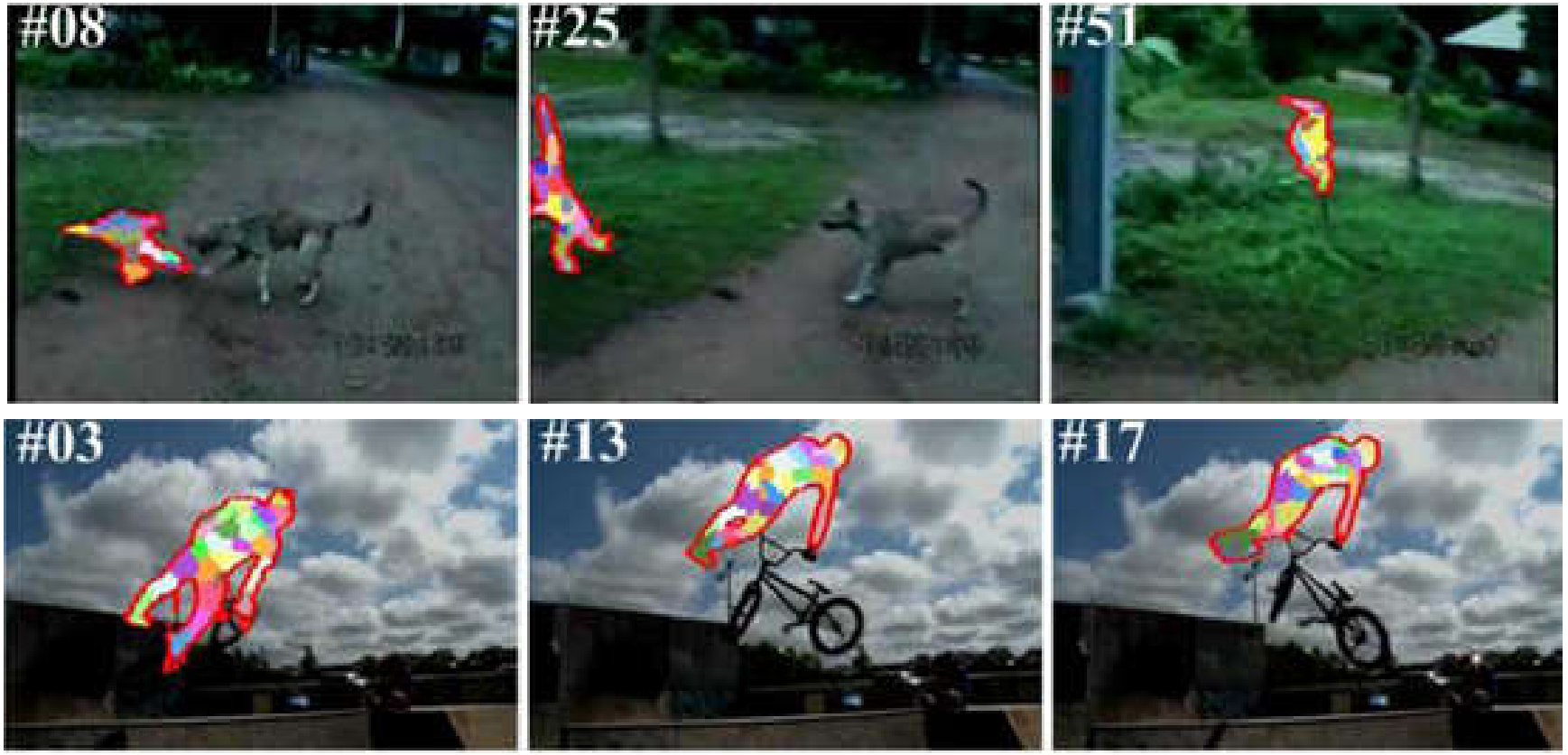


Image courtesy of [Wen'15]

Future Work: Proposal Selection Tracking

- Handle deformable objects
  - Select best candidates based on
    - Matching [Cho'14, Revaud'15]
    - Multi-hypothesis trajectory analysis [Lee'15]

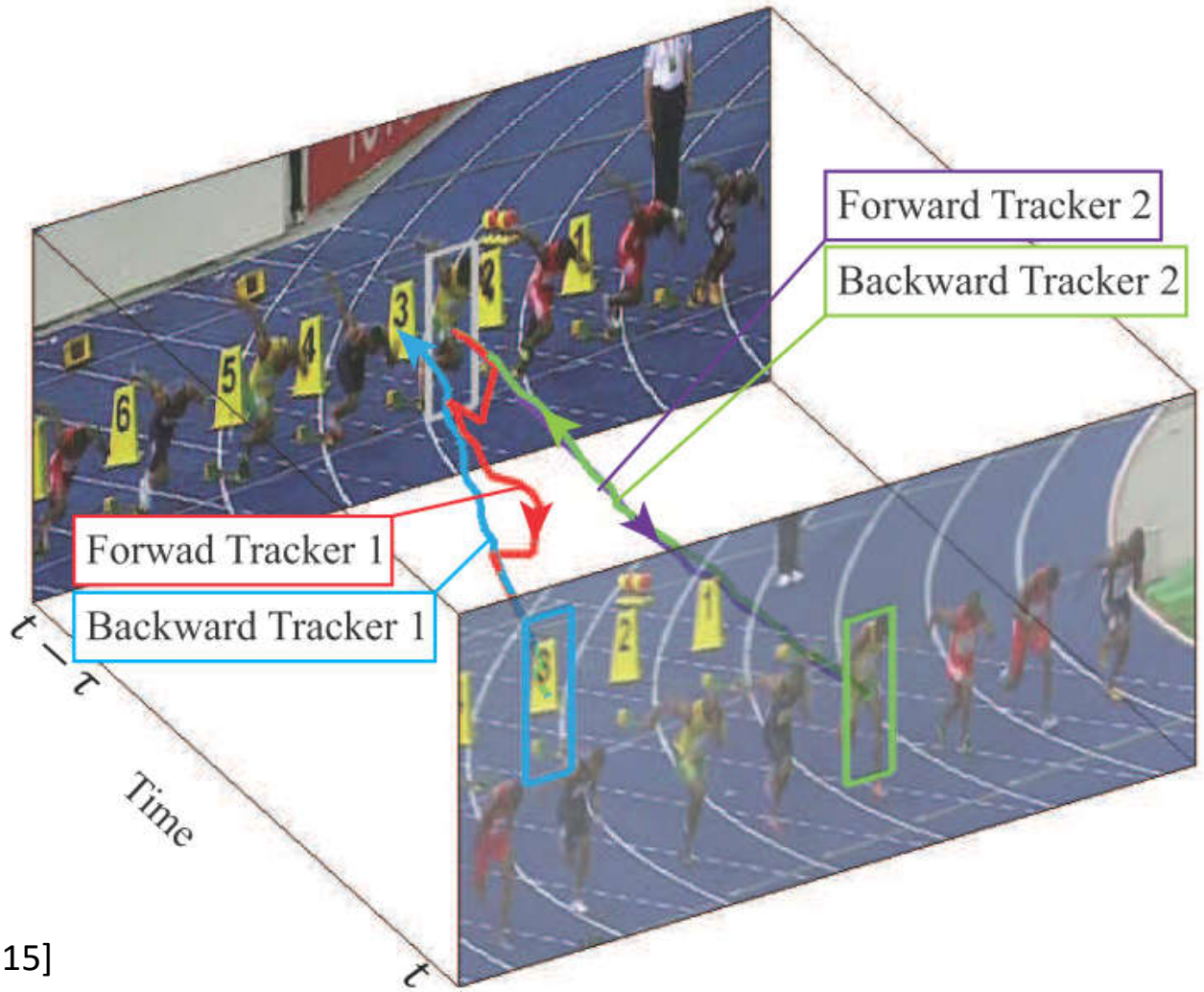


Image courtesy of [Lee'15]

Future Work: Occlusion and Motion Reasoning

- Utilize deep learning for motion representation
  - Learn motion patterns from video data
  - Learn to identify the state of the object
  - Harvest training data without violating model-free setting

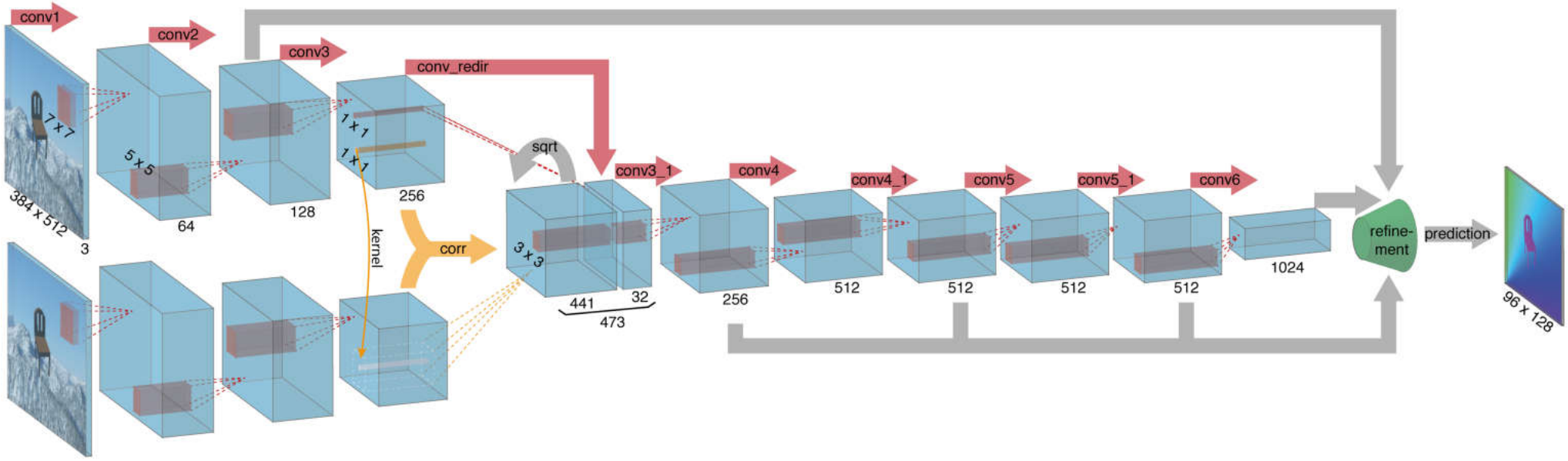


Image courtesy of [Dosovitskiy'15]

Thank You

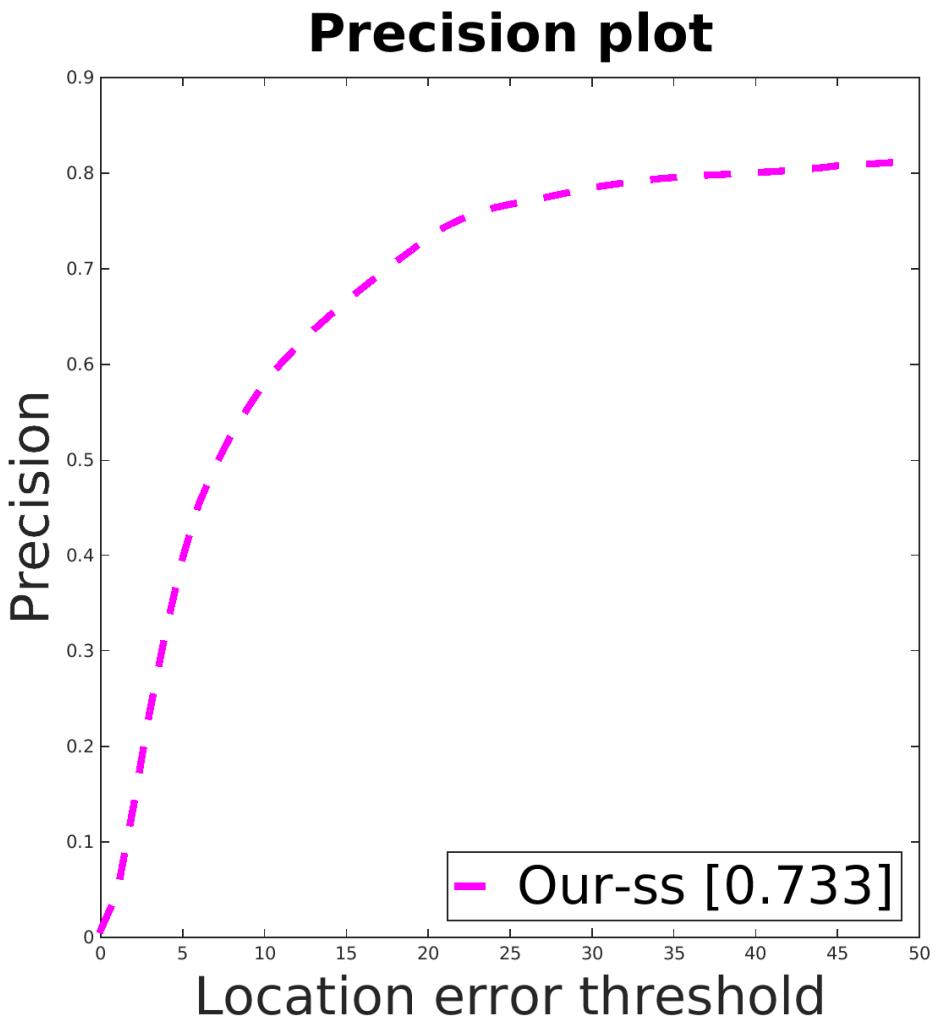
This PhD thesis is supported in part by the MSR-Inria joint project, Google Faculty Research Award, and the ERC advanced grant ALLEGRO

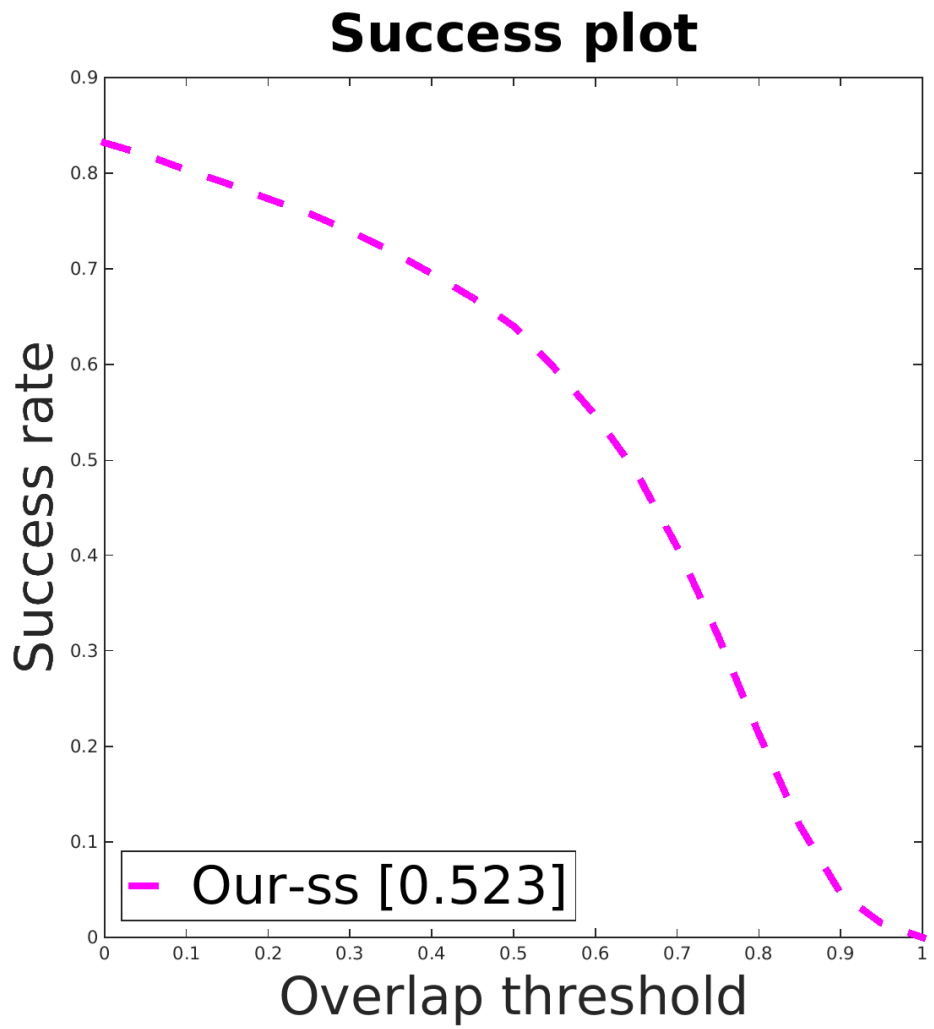
Appendix

- Experimental results: OTB (Precision & Success Plot)
- Experimental results: VOT2014
- Framework of simplified PST
- Experimental results: VOT2015
- Rank table of VOT2015 and VOT-TIR2015
- A brief review of tracking problems

Experimental Results

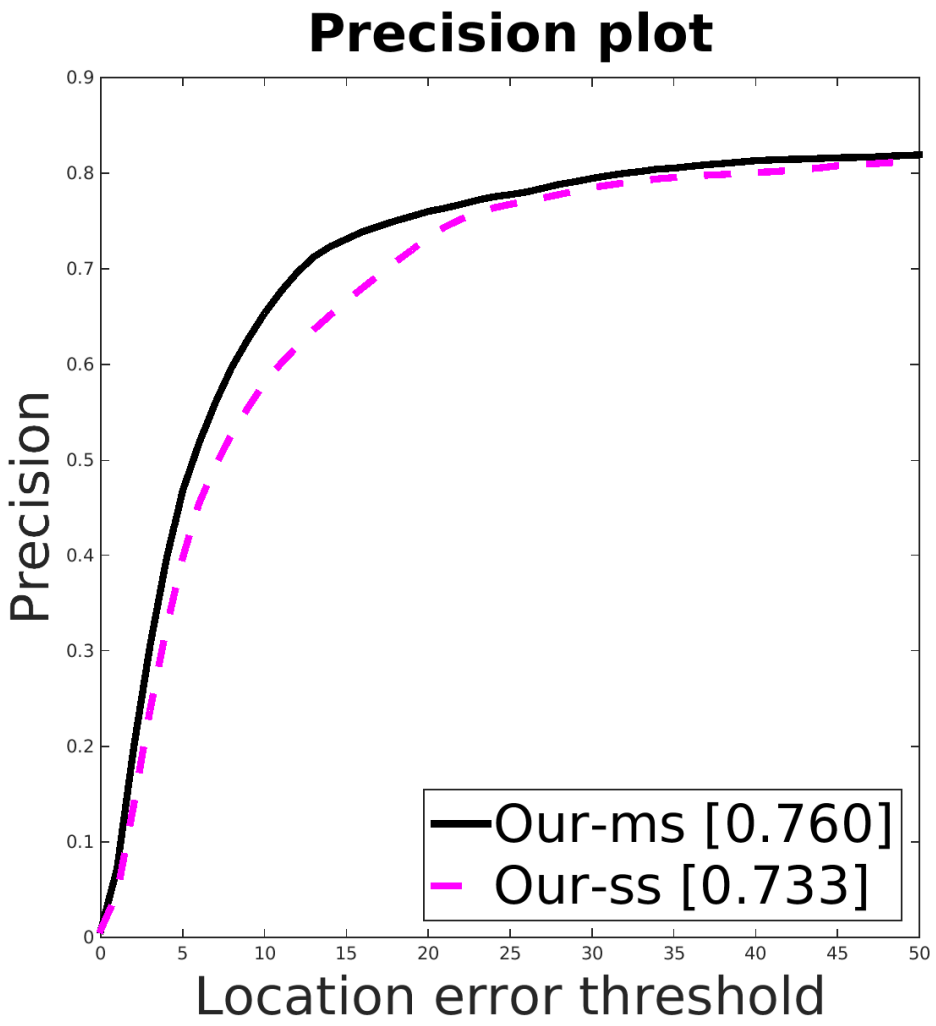
- Online Tracking Benchmark (OTB) Results: Our variants
  - Our-ss
    - Proposal: detection (single scale)
    - Selection: detection score

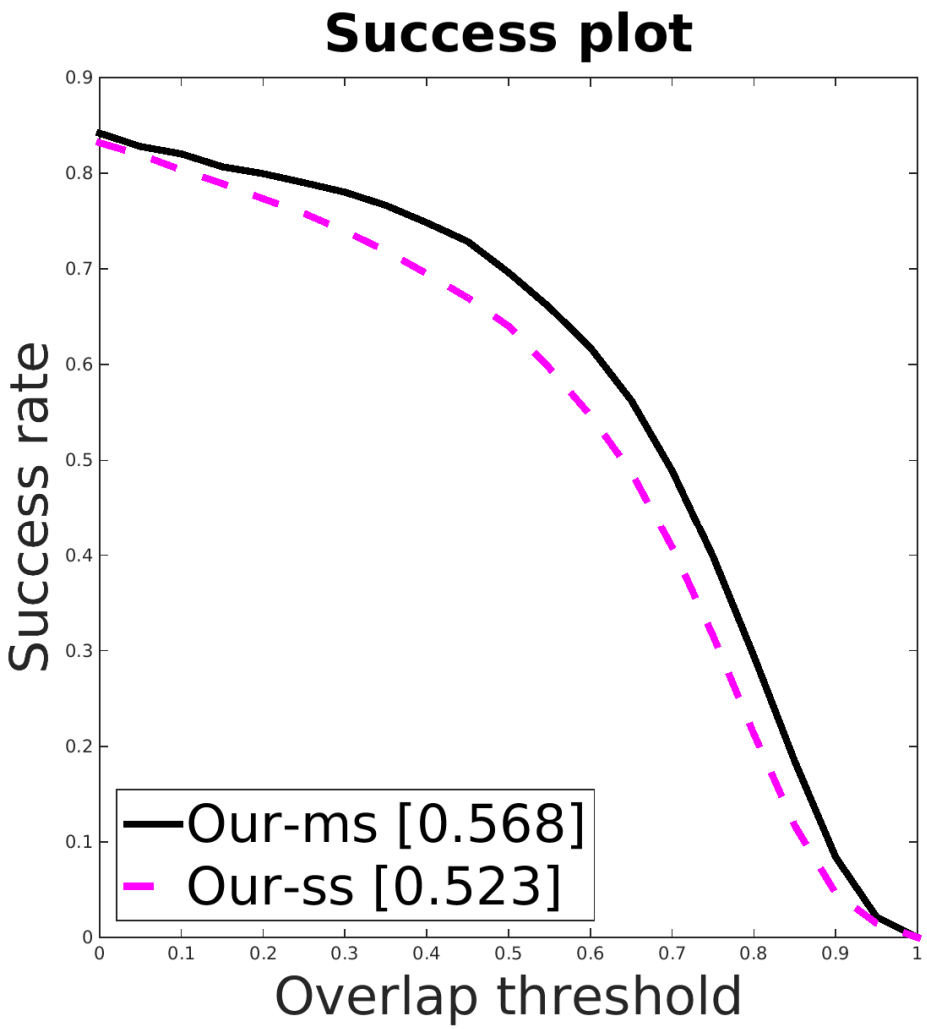




Experimental Results

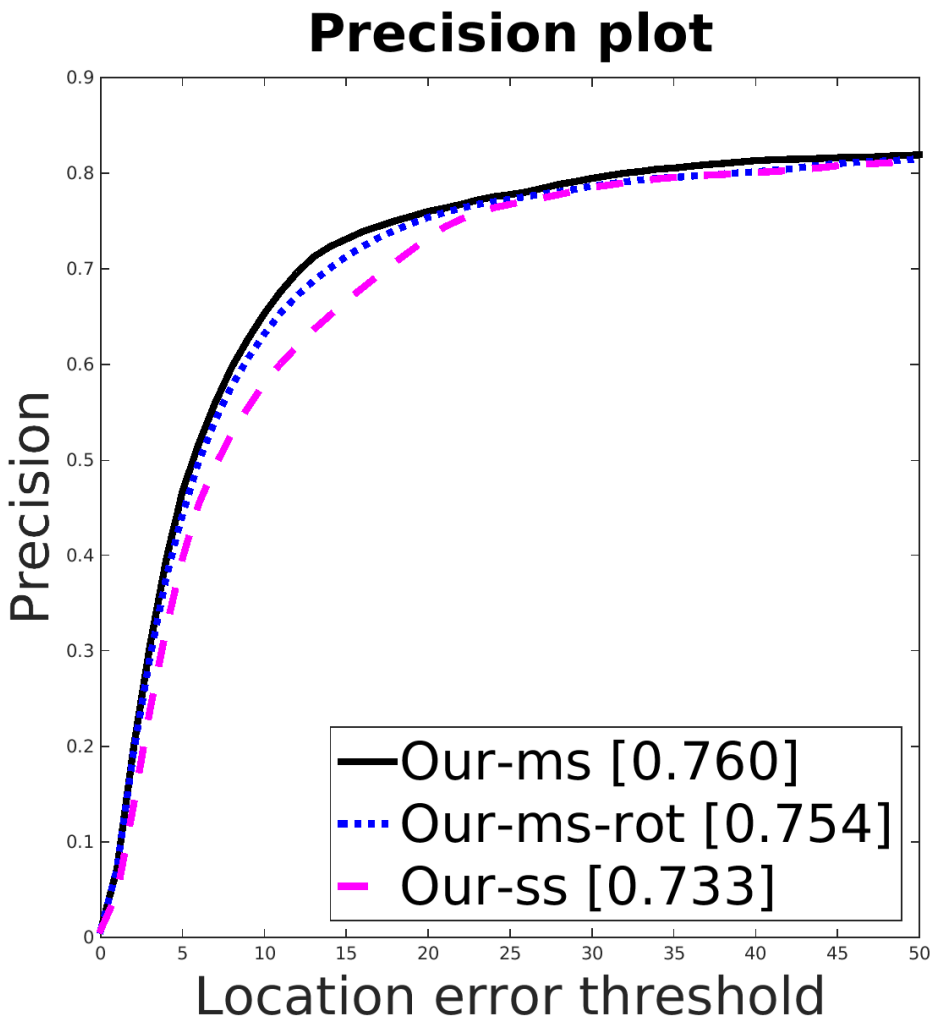
- Online Tracking Benchmark (OTB) Results: Our variants
  - Our-ms
    - Proposal: detection (multiple scales)
    - Selection: detection score

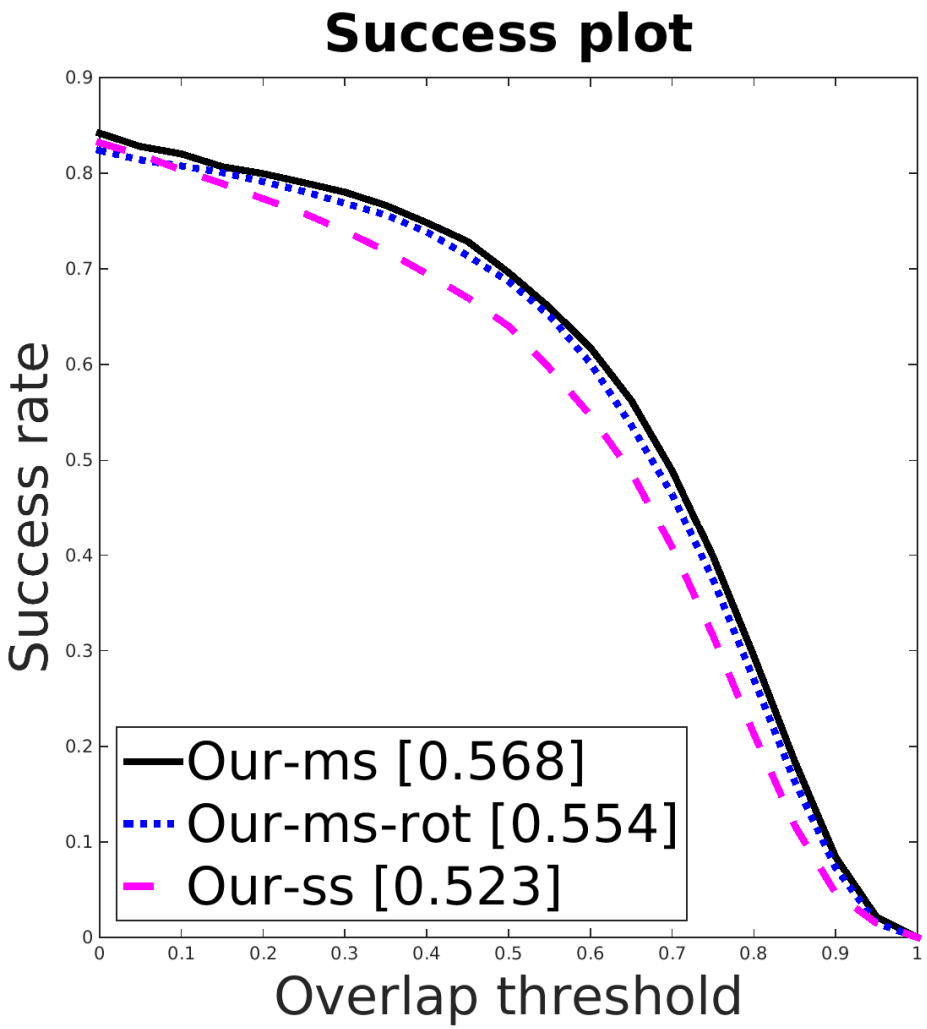




Experimental Results

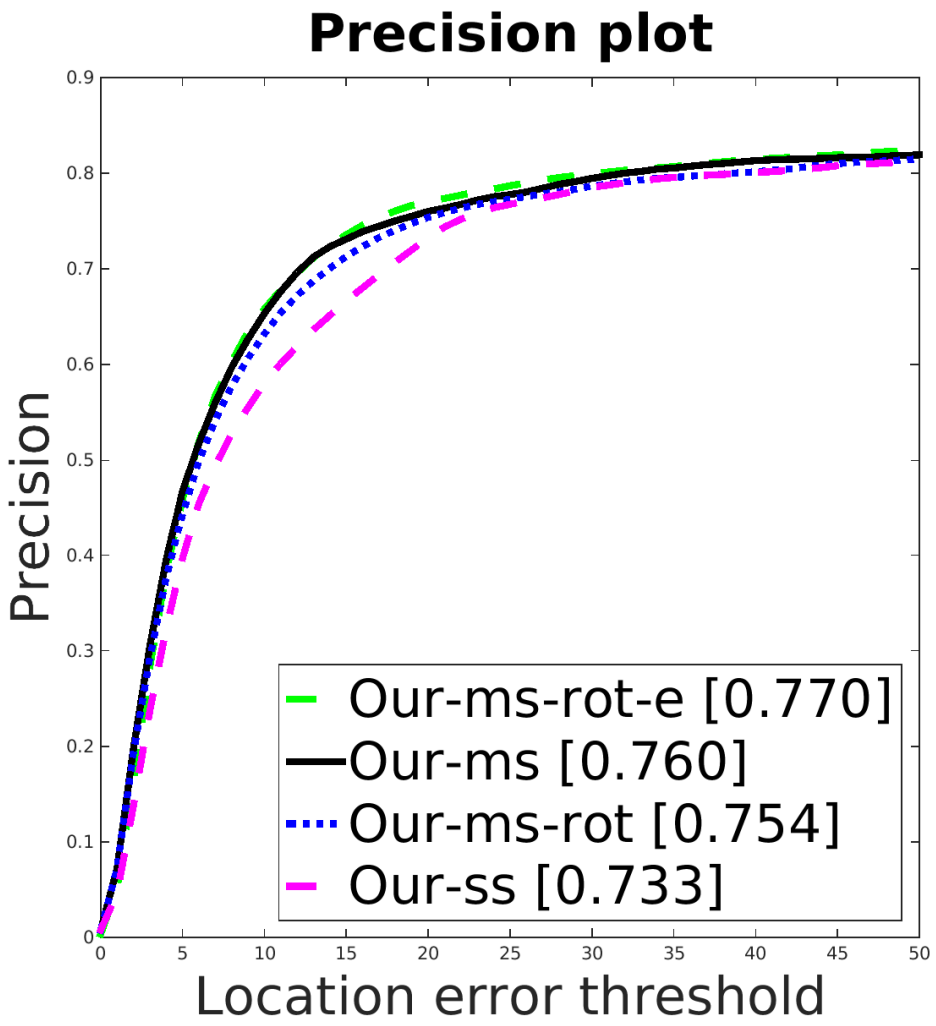
- Online Tracking Benchmark (OTB) Results: Our variants
  - Our-ms-rot
    - Proposal: detection (multiple scales) + geometry
    - Selection: detection score

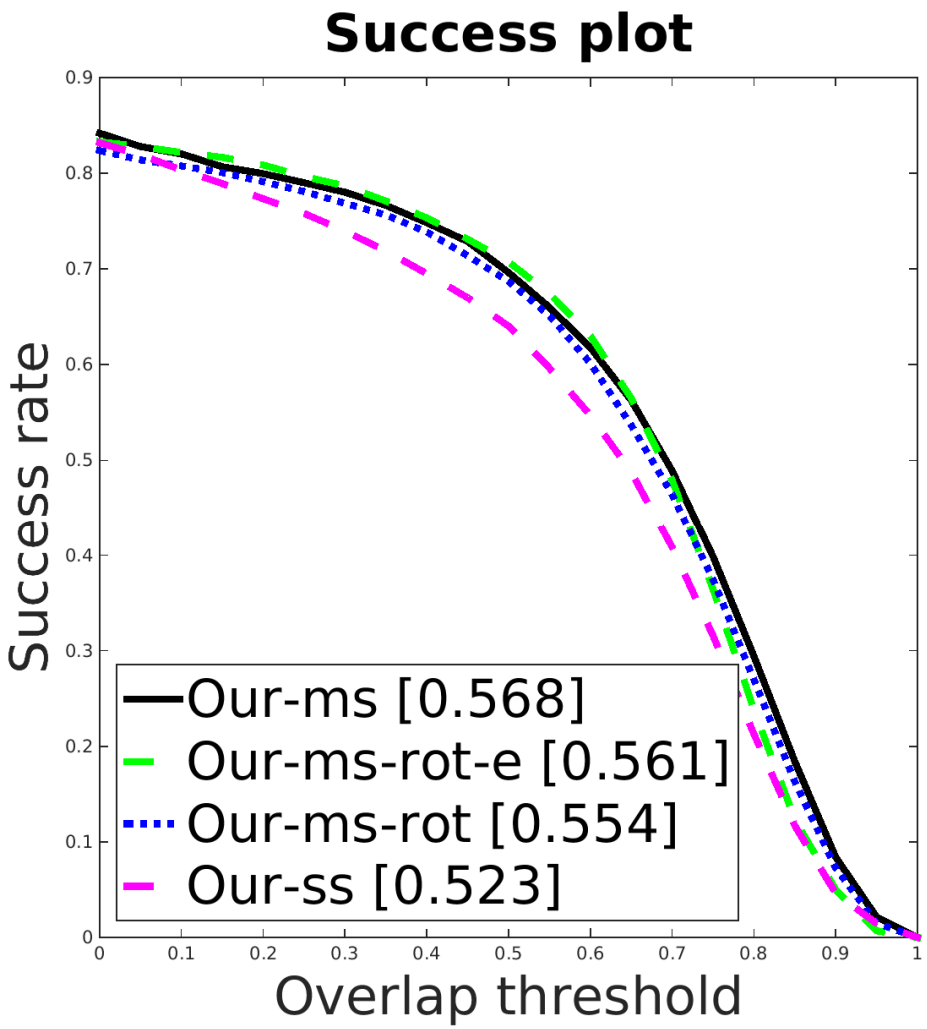




Experimental Results

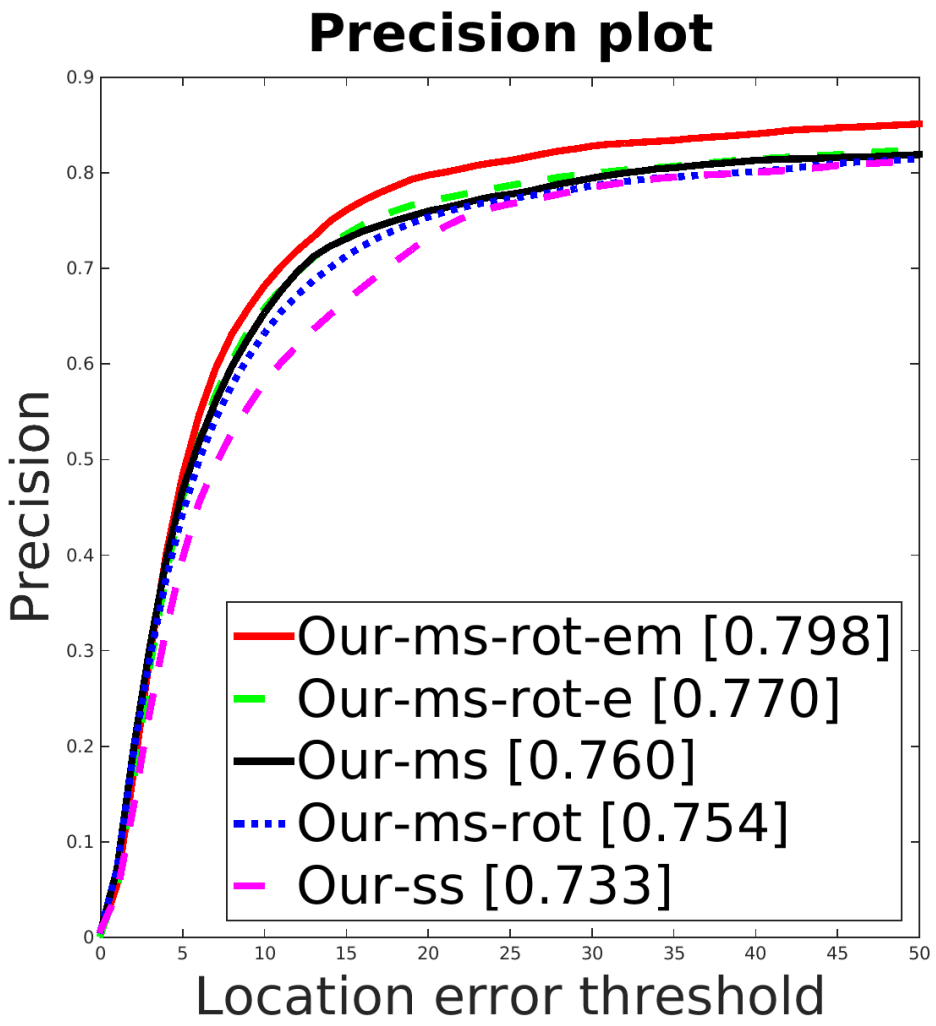
- Online Tracking Benchmark (OTB) Results: Our variants
  - Our-ms-rot-e
    - Proposal: detection (multiple scales) + geometry
    - Selection: detection + edgebox (edge response) scores

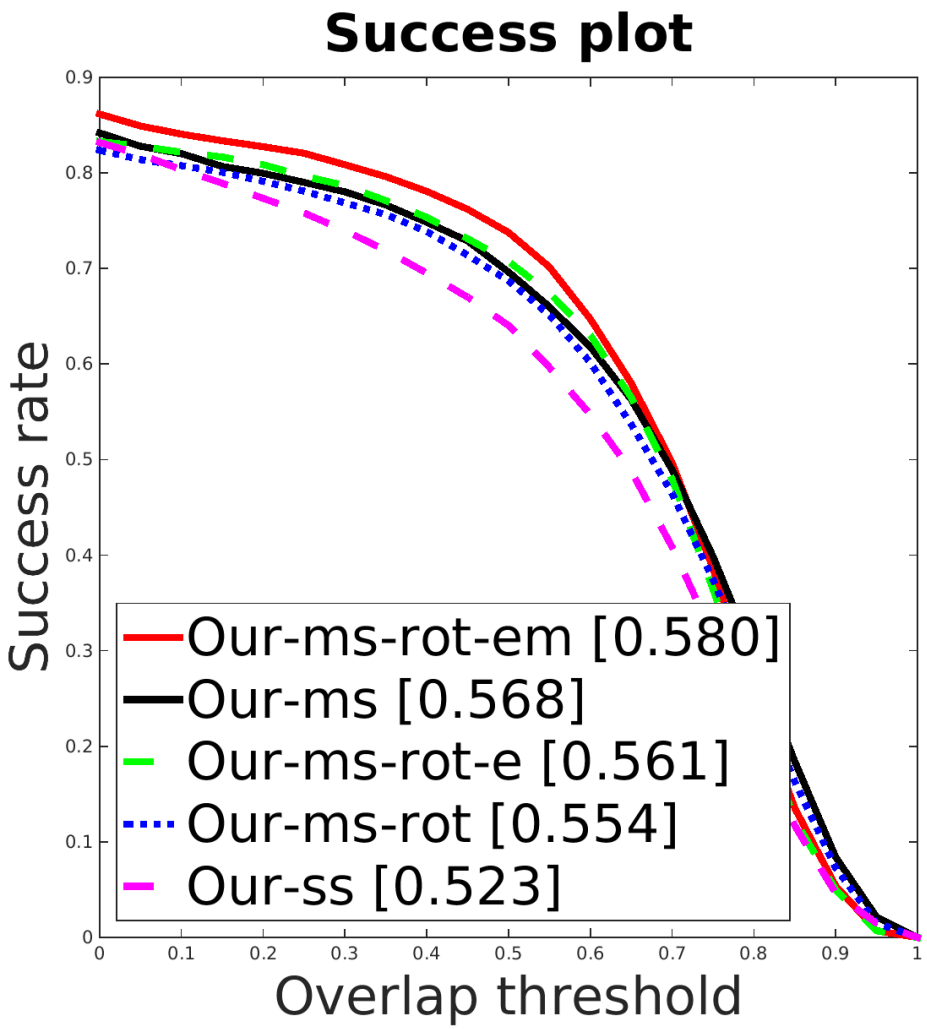




Experimental Results

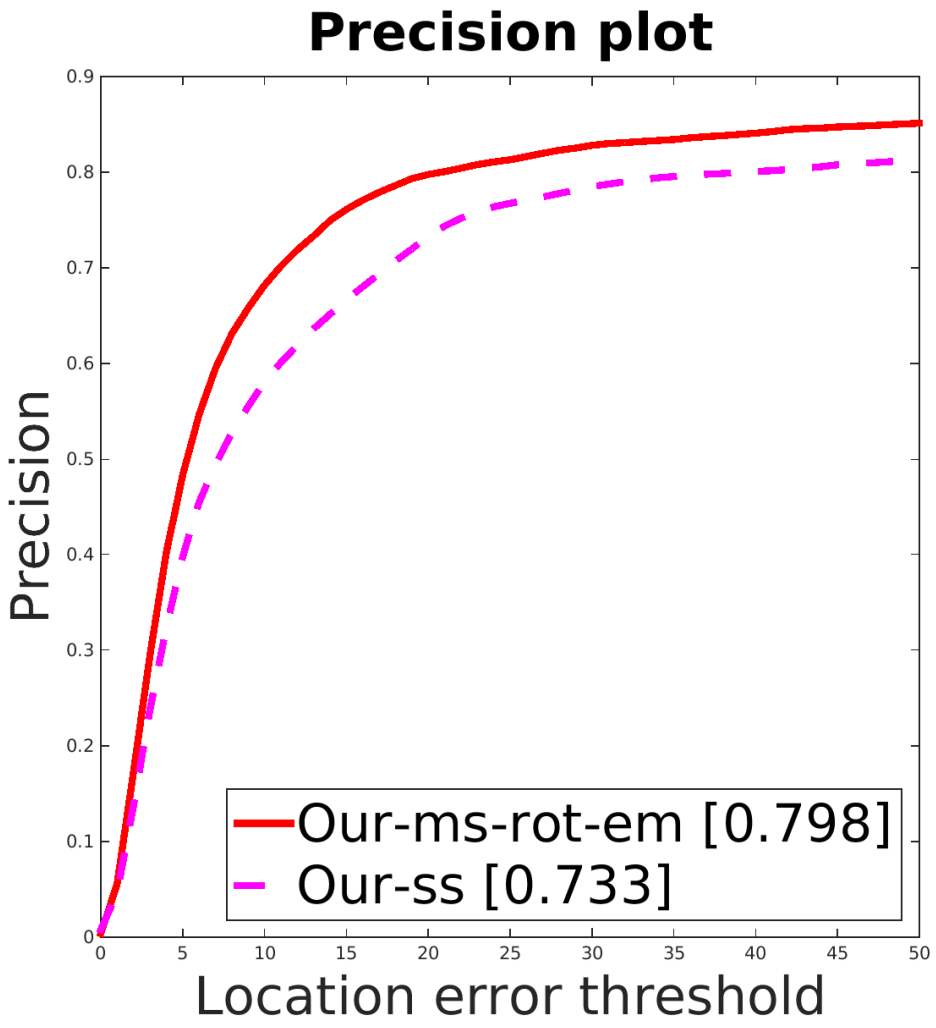
- Online Tracking Benchmark (OTB) Results: Our variants
  - Our-ms-rot-em
    - Proposal: detection (multiple scales) + geometry
    - Selection: detection + edgebox (edge & motion boundary response)

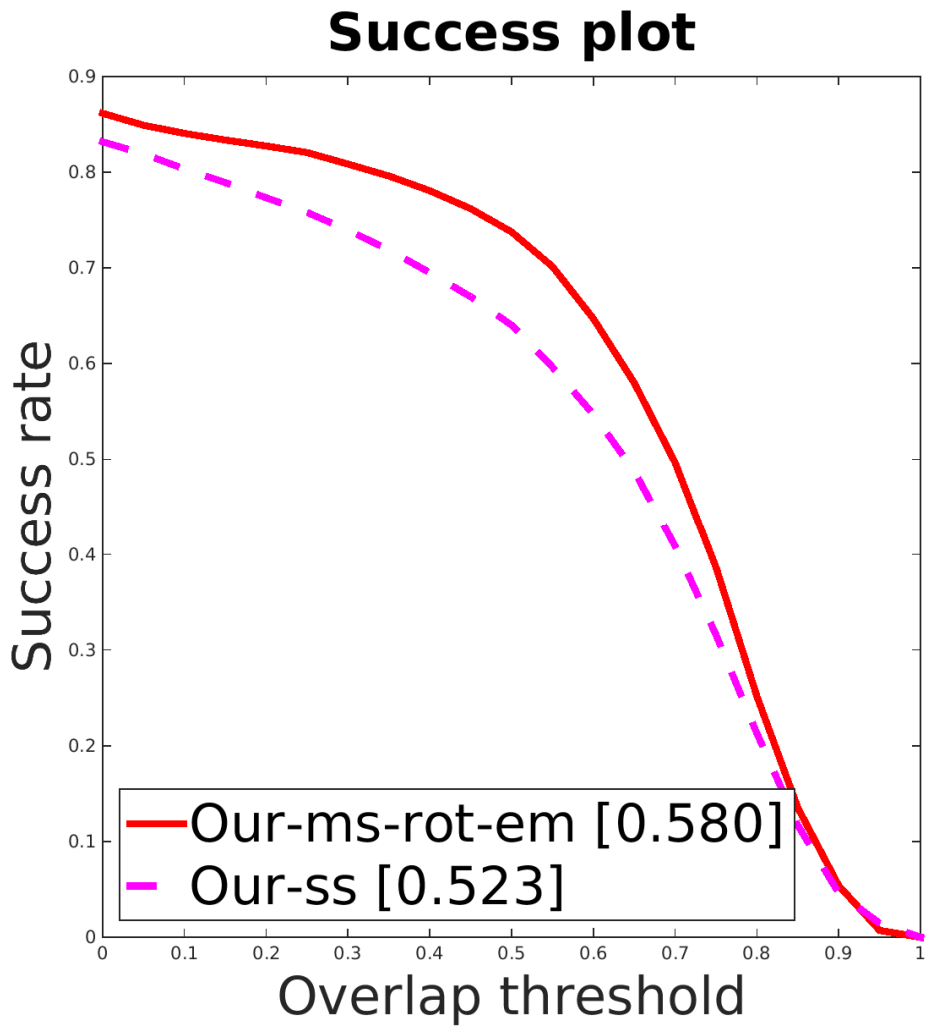




Experimental Results

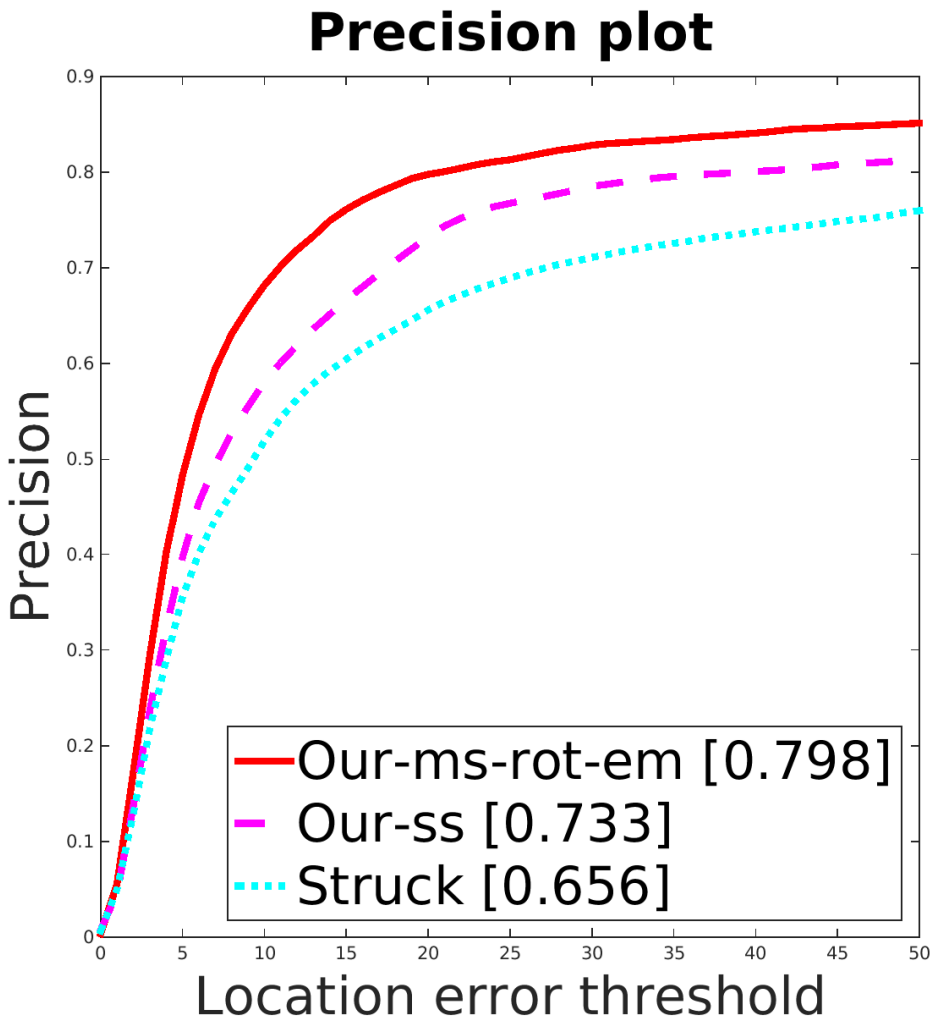
- Online Tracking Benchmark (OTB) Results: Ours vs. others

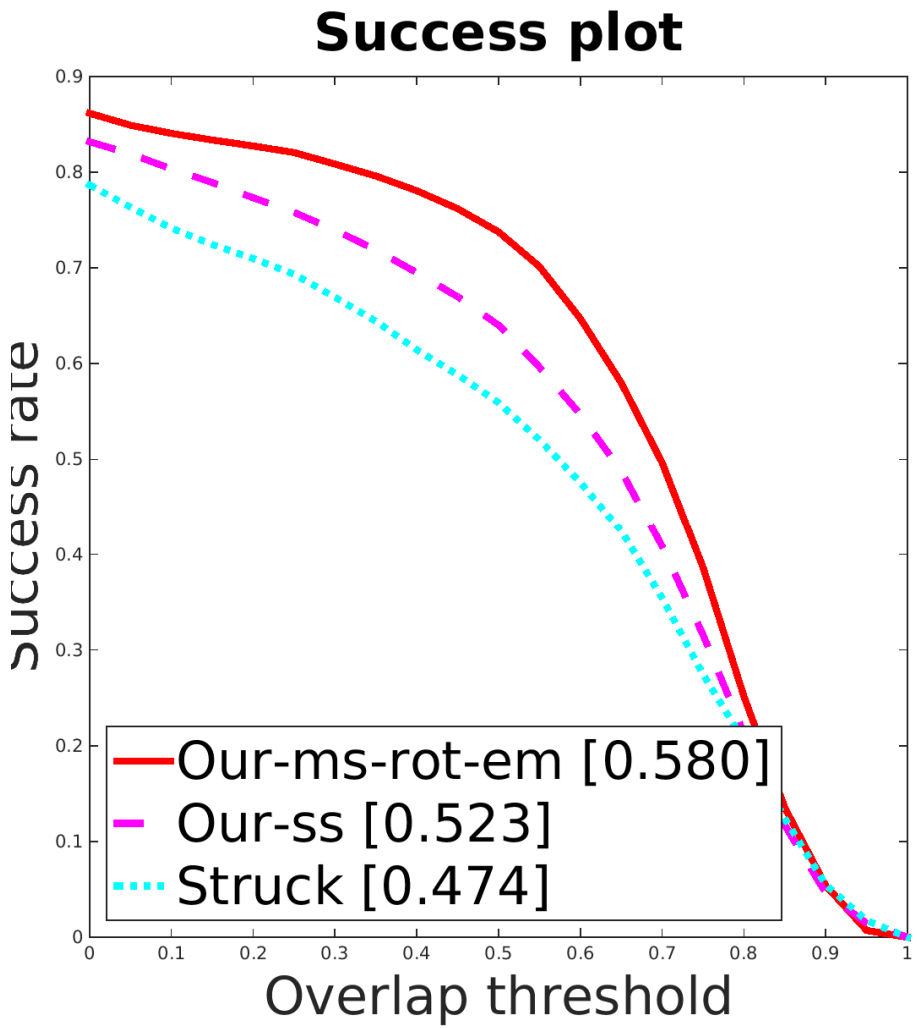




Experimental Results

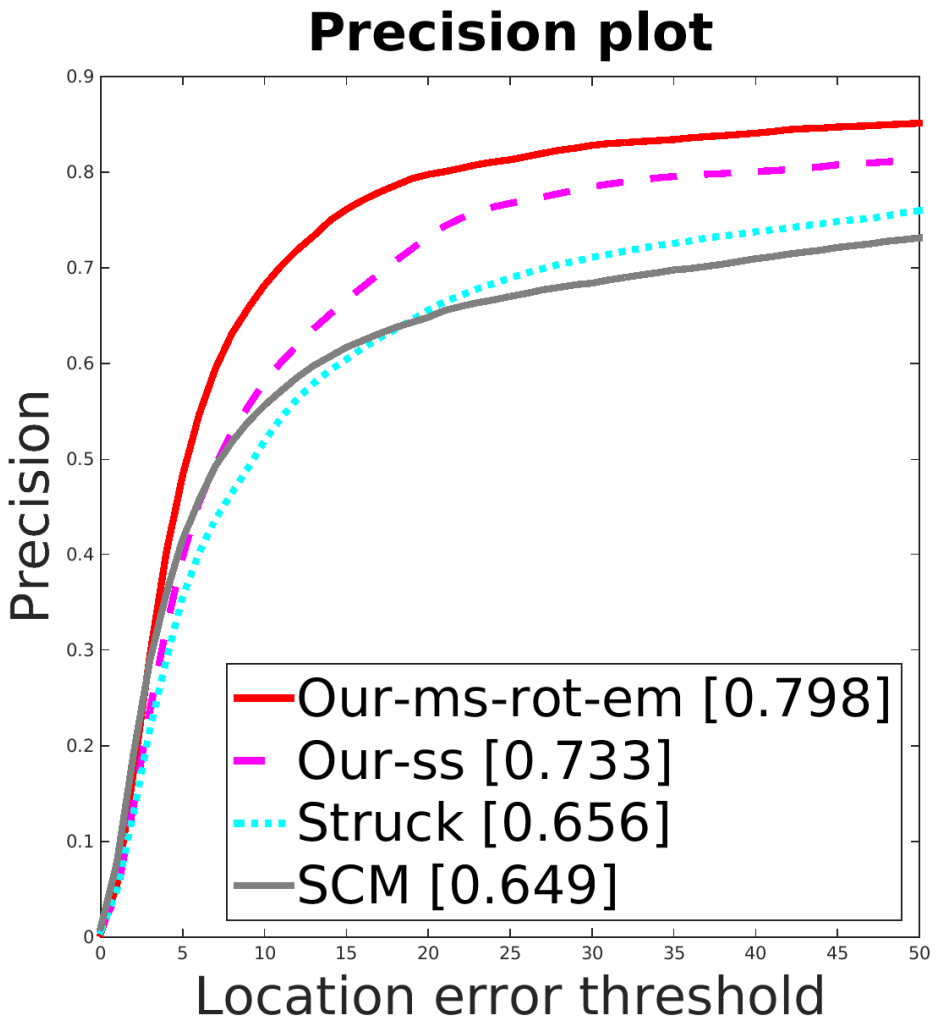
- Online Tracking Benchmark (OTB) Results: Ours vs. others

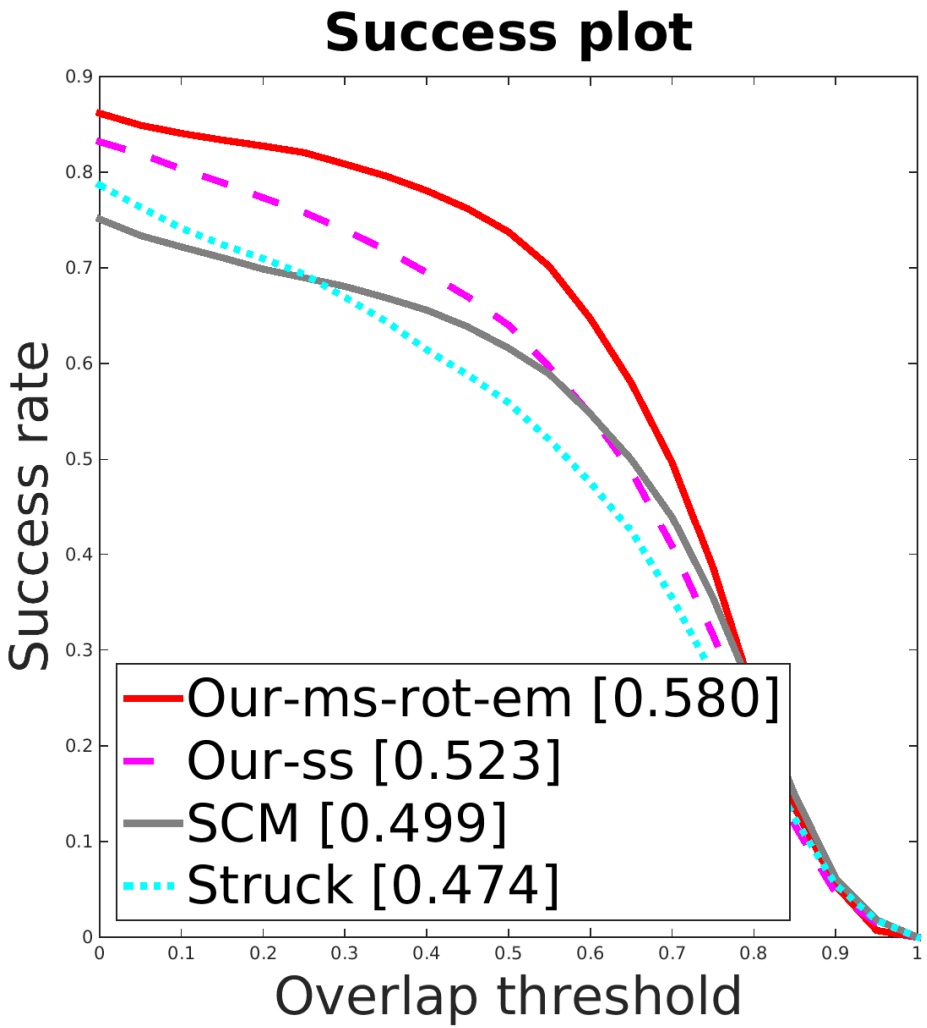




Experimental Results

- Online Tracking Benchmark (OTB) Results: Ours vs. others



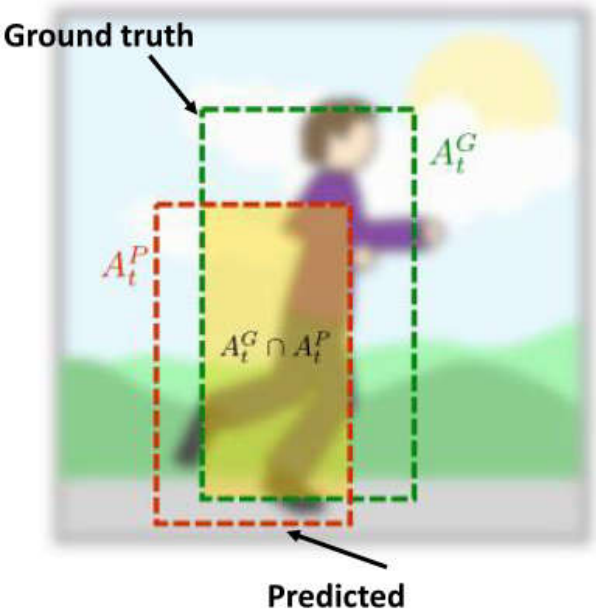


Experimental Results

- Visual Object Tracking (VOT) 2014 Challenge Dataset (25 seq.)
  [Kristan'14]

Experimental Results

- Visual Object Tracking (VOT) 2014 Challenge Evaluation Metrics
  - Accuracy: Average overlap during successful tracking
  - Robustness: Number of times a tracker drifts off the target



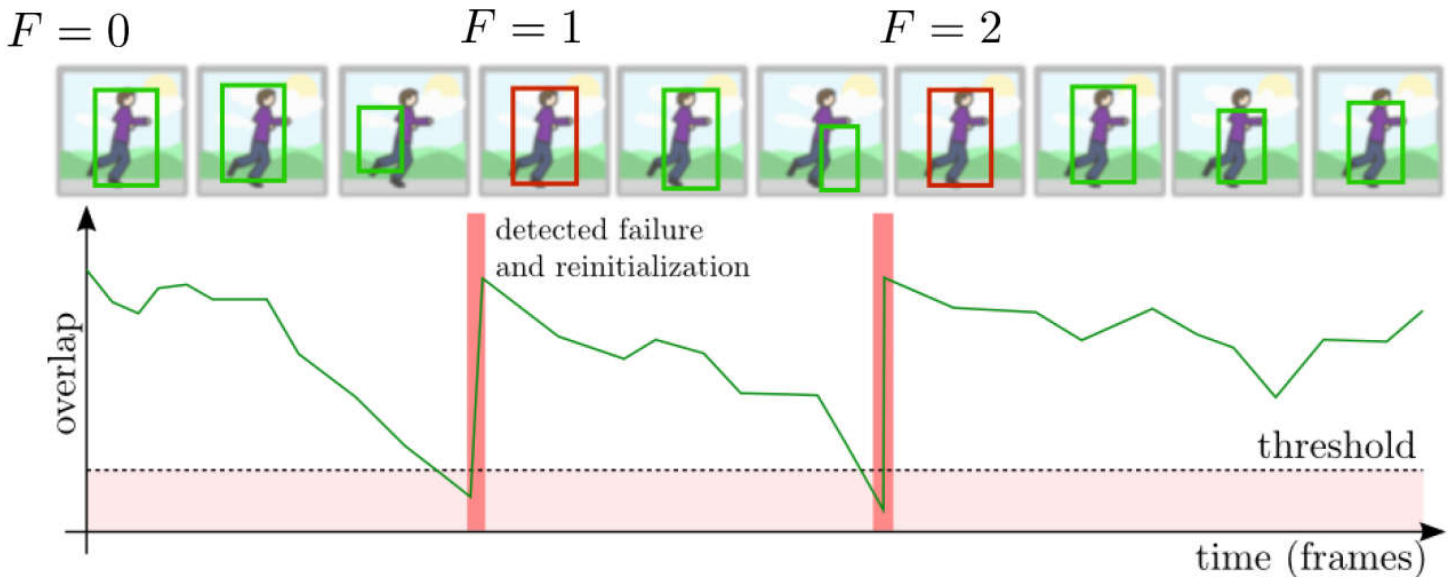
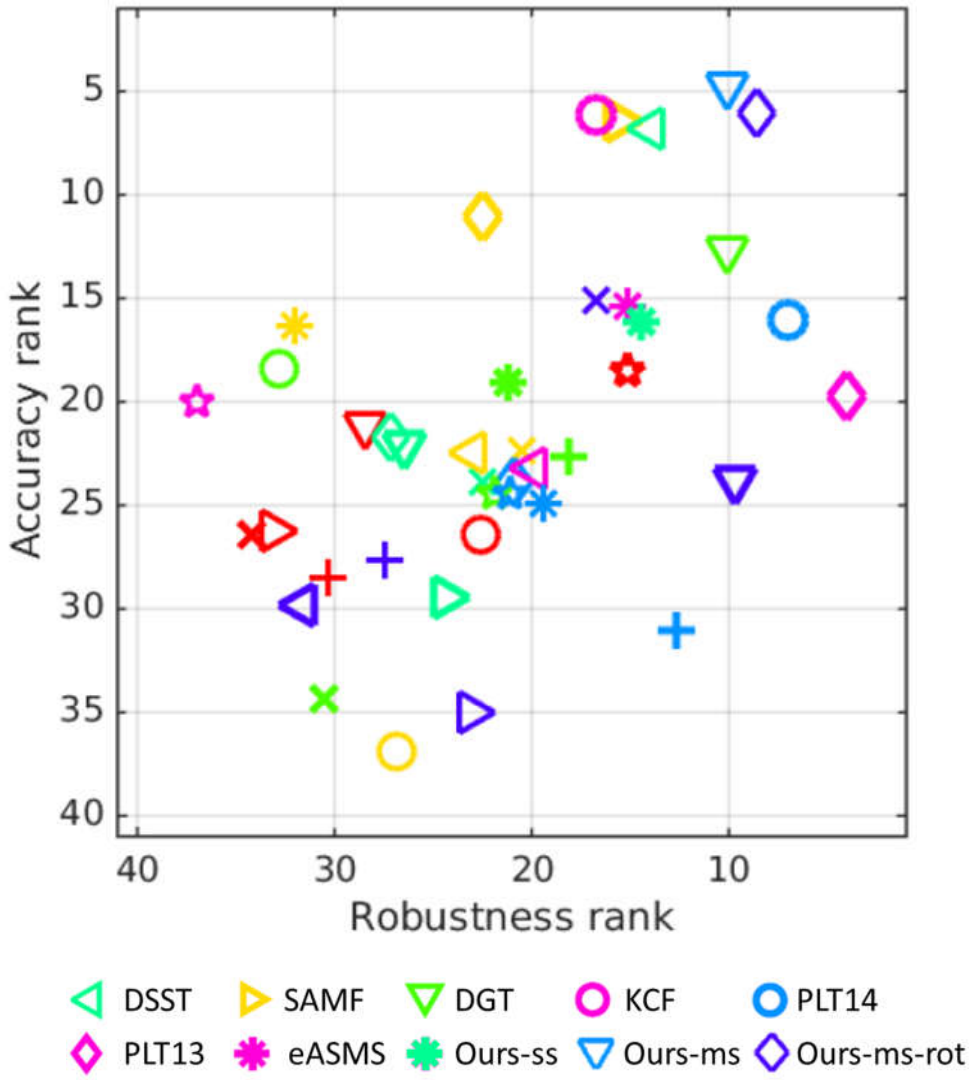


Image courtesy of [Kristan'14]

Experimental Results

- Visual Object Tracking (VOT) 2014 Challenge Results

Method	Accuracy	Robust.	Average
Our-ms-rot	**6.07**	**8.58**	**7.33**
Our-ms	**4.73**	10.13	**7.43**
DSST	6.78	13.99	**10.39**
SAMF	6.46	15.65	11.06
DGT	12.67	10.13	11.40
KCF	**6.16**	16.71	11.44
PLT14	16.04	**6.98**	11.51
PLT13	19.74	**4.00**	11.87
eASMS	15.37	15.10	15.24
Our-ss	16.11	14.47	15.29



Experimental Results

- Visual Object Tracking (VOT) 2014 Challenge Results

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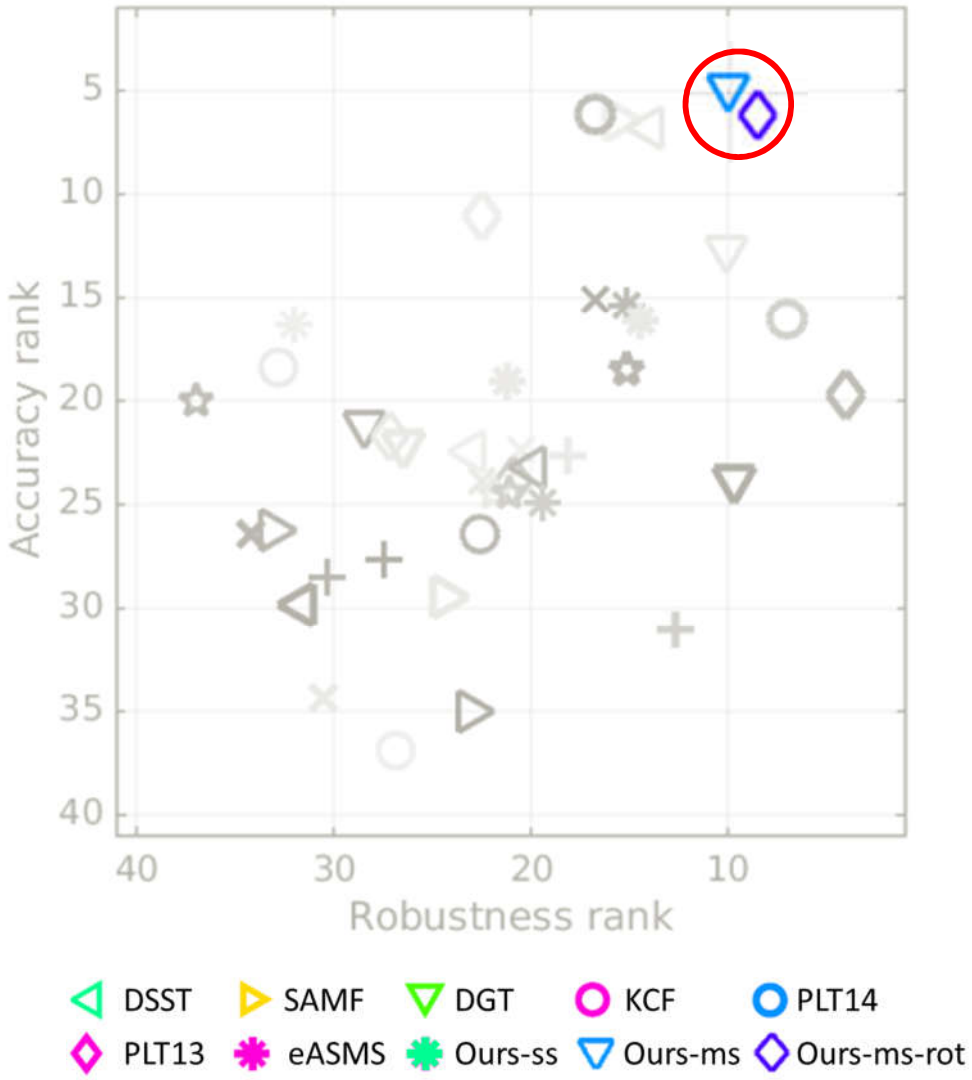
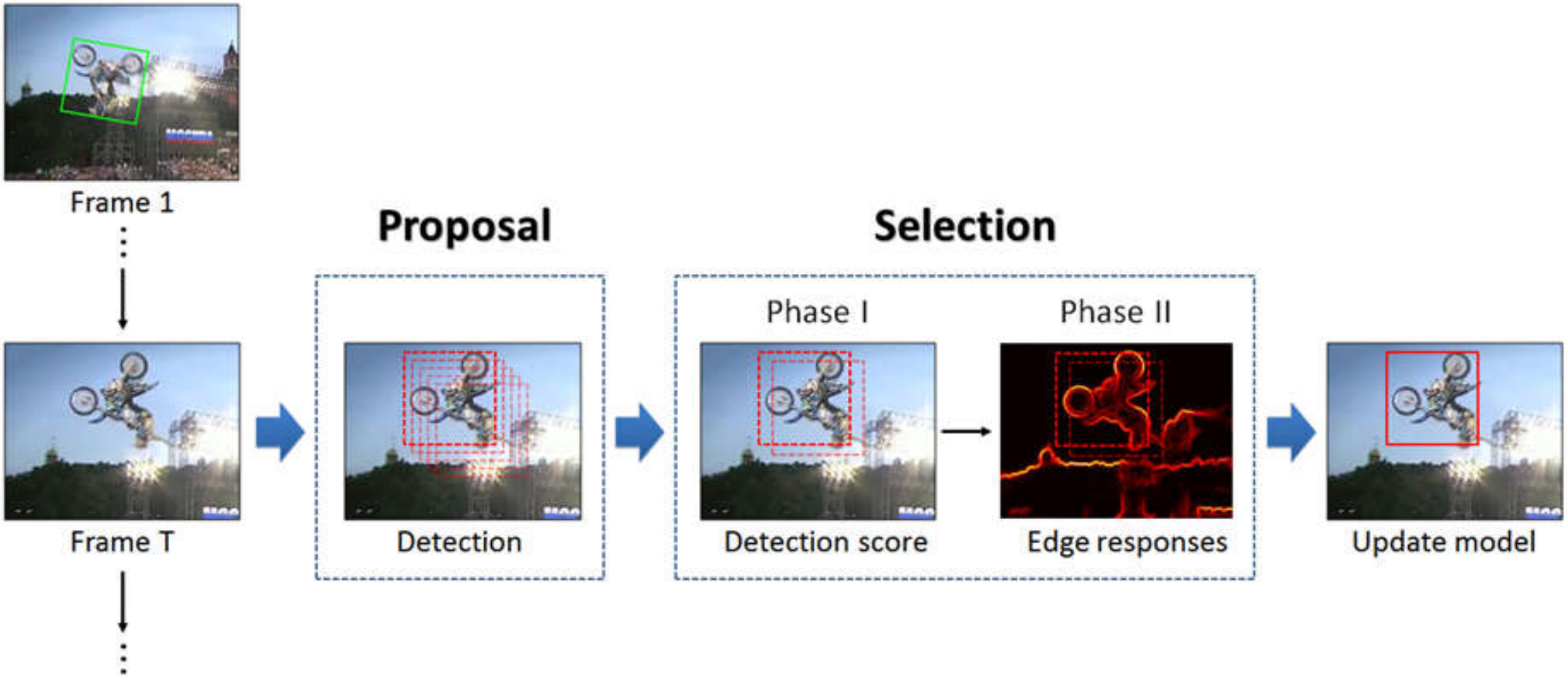
eASMS	15.37	15.10	15.24
Our-ss	16.11	14.47	15.29



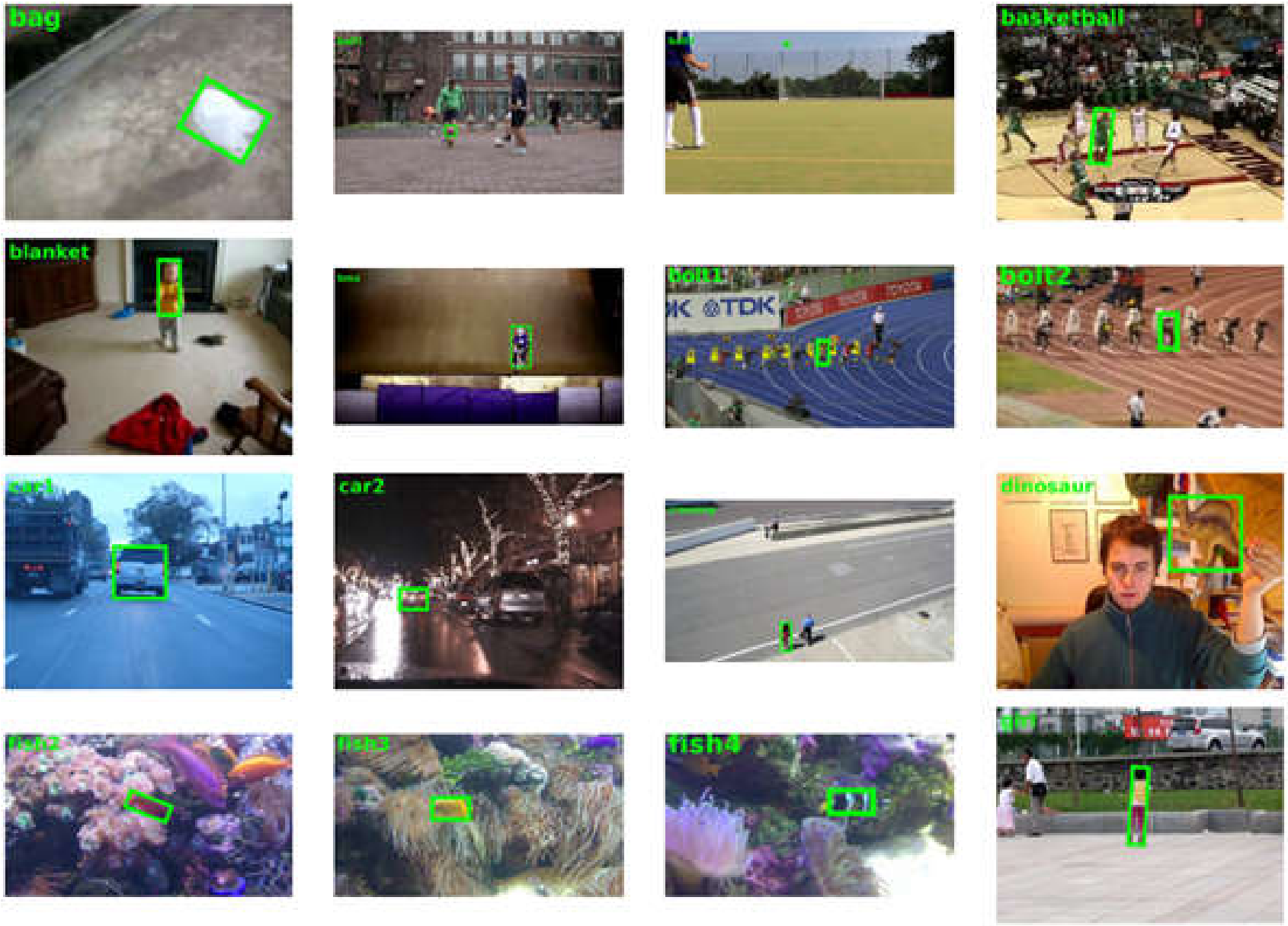
Experimental Results

- Participated in VOT competitions with a simplified Proposal Selection Tracking framework



Experimental Results

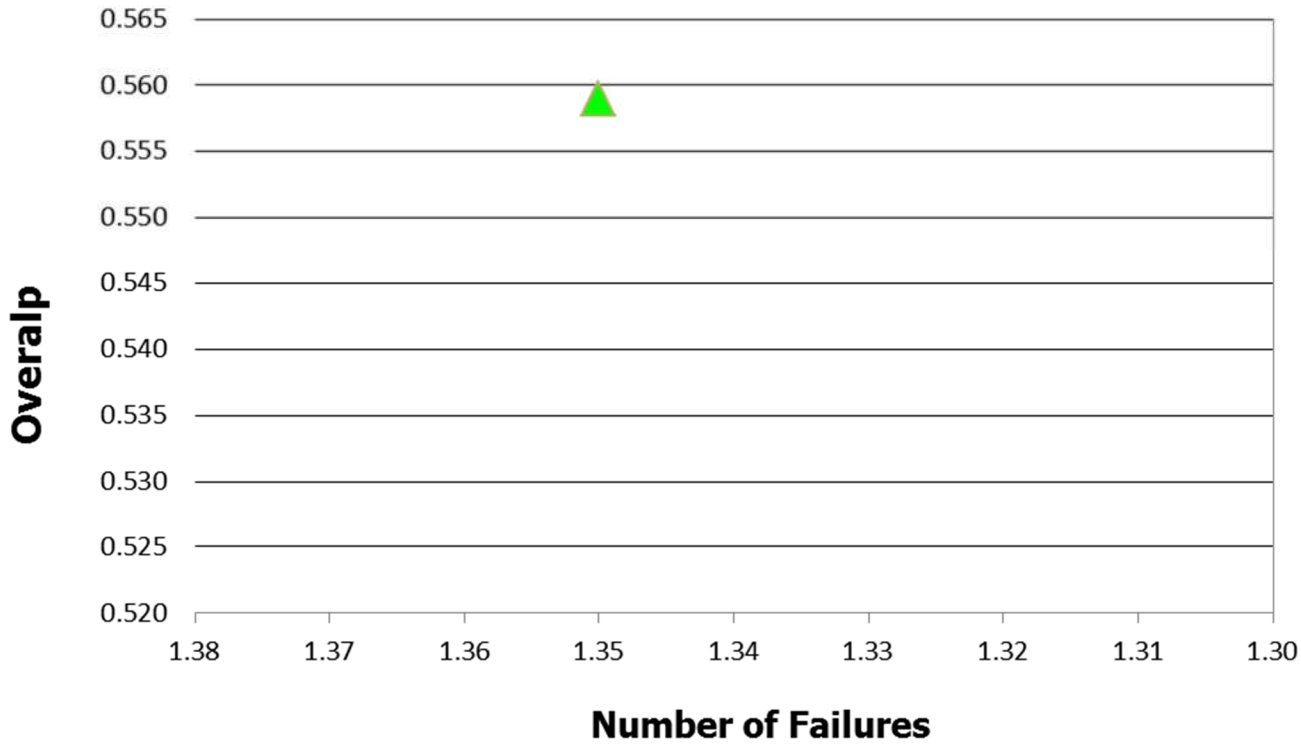
- Visual Object Tracking (VOT) 2015 Challenge Dataset (60 seq.) [Kristan'15]



Experimental Results

- Visual Object Tracking (VOT) 2015 Challenge Results

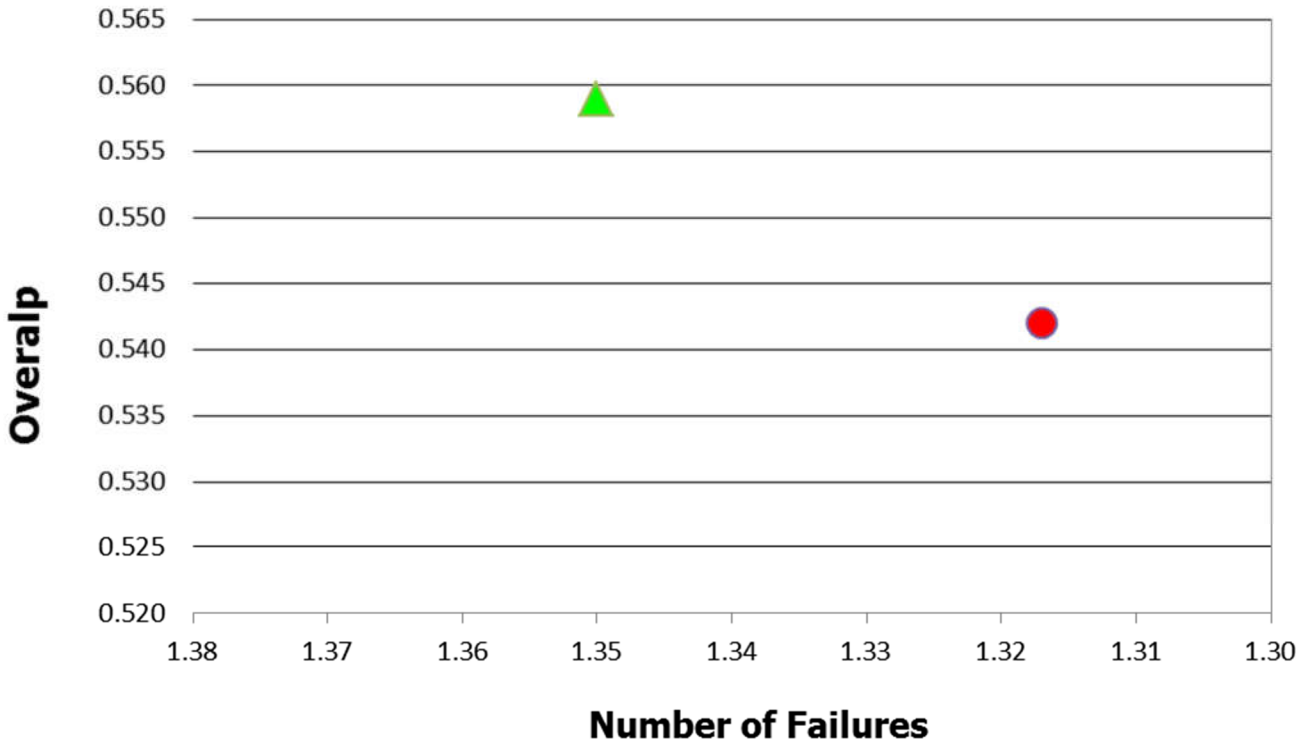
▲ Selection: detection score only	
Acc. (Overlap)	Rob. (#Failures)
0.559	1.35



Experimental Results

- Visual Object Tracking (VOT) 2015 Challenge Results

▲ Selection: detection score only		● Selection: detection + edgebox score	
Acc. (Overlap)	Rob. (#Failures)	Acc. (Overlap)	Rob. (#Failures)
0.559	1.35	0.542	**1.32**



Experimental Results

- Rank table of VOT2015 Challenge Results

Method	Accuracy	Robust.	Φ
MDNet*	**0.60**	**0.69**	**0.38**
DeepSRDCF*	0.56	**1.05**	**0.32**
EBT	0.47	**1.02**	**0.31**
SRDCF*	0.56	1.24	0.29
LDP*	0.52	1.84	0.28
sPST*	0.55	1.48	0.28
SC-EBT	0.55	1.86	0.25
NSAMF*	0.53	1.29	0.25
Struck*	0.47	1.61	0.25
RAJSSC	**0.57**	1.63	0.24

Φ: Expected average overlap

Experimental Results

- Rank table of VOT-TIR2015 Challenge Results

Method	Accuracy	Robust.	Φ
SRDCFir*	0.65	0.58	0.70
sPST*	0.66	2.18	0.64
MCCT*	0.67	3.34	0.55
EBT	0.50	3.50	0.43
CCFP*	0.63	8.55	0.36
ABCD*	0.63	5.81	0.34
Struck*	0.58	8.48	0.30

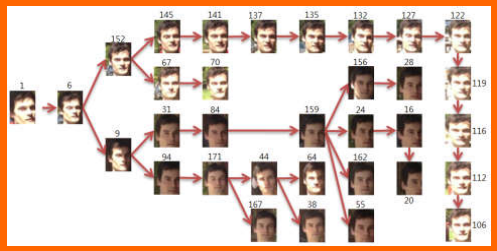
Φ: Expected average overlap

Visual Object Tracking: A brief history (problems)

Point Tracking
[Sethi and Jain, 1987, Salari and Sethi, 1990]

Multiple Cameras Tracking
[Stauffer and Tieu, 2003]

Offline/Non-causal Tracking
[Black and Jepson, 1998, Hong and Han, 2014]



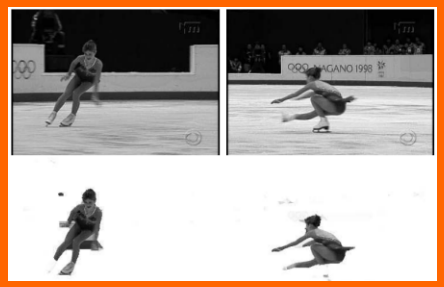
RGBD Tracking
[Song and Xiao, 2013]

1950s ▶ Now

Model-Specific Tracking
[Wren et al., 1997]

Multiple objects Tracking
[Bose et al., 2007]

Non-rigid Object Tracking
[Ren and Malik, 2007]



Long-term Tracking
[Kalal, Mikolajczyk and Matas, 2012]