Deep Learning for Visual Tracking

T. Chateau

Credits:
Marvasti-Zadeh, Seyed Mojtaba, Li Cheng, Hossein Ghanei-Yakhdan, et Shohreh Kasaei. « Deep Learning for Visual Tracking: A Comprehensive Survey ». CoRR abs/1912.00535 (2019). http://arxiv.org/abs/1912.00535.

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Deep Learning for Visual Tracking

What is Visual Tracking? From single view single object

Deep Learning for Visual Tracking

What is Visual Tracking? To multi view Muti-non rigid-objects

Deep Learning for Visual Tracking

What is Visual Tracking?

State Vector

The dynamic configuration of the the tracked object at time k is modelled by a State vector denoted:

$$\mathbf{x}_k$$

State Sequence

The state sequence is given by the set (sequence) of State vectors, denoted:

$$\mathbf{X} \doteq \{\mathbf{x}_k\}_{k=1,\ldots,K}$$

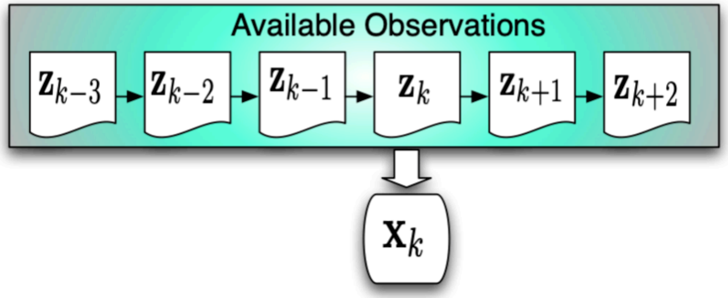
Observation

Observation: $\mathbf{Z} \doteq \{\mathbf{z}_k\}_{k=1,\ldots,K}$

Deep Learning for Visual Tracking

Off-line Tracking (Deferred Tracking)

Estimation of the state $\mathbf{x}_k$ uses the entire observation sequence $\mathbf{Z} \doteq \{\mathbf{z}_k\}_{k=1,\dots,K}$



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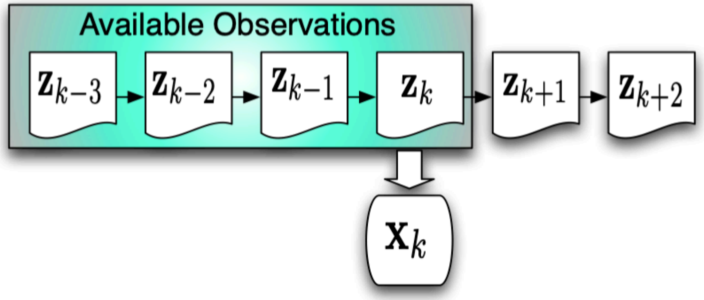
On-line Tracking

Estimation of the state $\mathbf{x}_k$ uses the current and past observation: $\mathbf{z}_{0:k}$



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Why is Visual Tracking difficult?

Hidden State

The state $\mathbf{X}$ is a hidden state and must be deduced from observation

Tracking Challenges

- Object Modeling: how to define what an object is in terms that can be interpreted by a computer ?
- Appearance Change: The observation of an object changes according to many parameters (illumination conditions, occlusions, shape variation...)
- Kinematic Modelling: How to inject priors on object kinematic and interactions between objects.

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Why is Visual Tracking difficult? (Object representation)

- Object approximation:
  - Segmentation / Polygonal approximation
  - Bounding ellipse/box
  - Position only
- Goal: Measure affinity

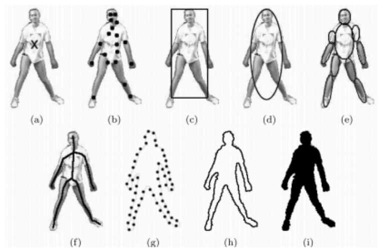

Image from A. Yilmaz et. Al : Object tracking: A survey. ACM Computing Surveys, 2006

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Why is Visual Tracking difficult? (Appearance change)

Variation des points de vue

Conditions de luminosité

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Why is Visual Tracking difficult? (Appearance change)

scale variation

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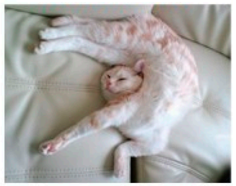
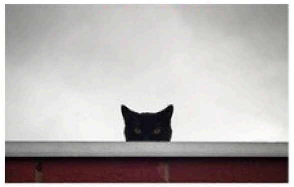
Why is Visual Tracking difficult? (Appearance change)

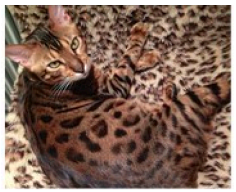
deformable object



occluded object



background confusion



intra-class variation

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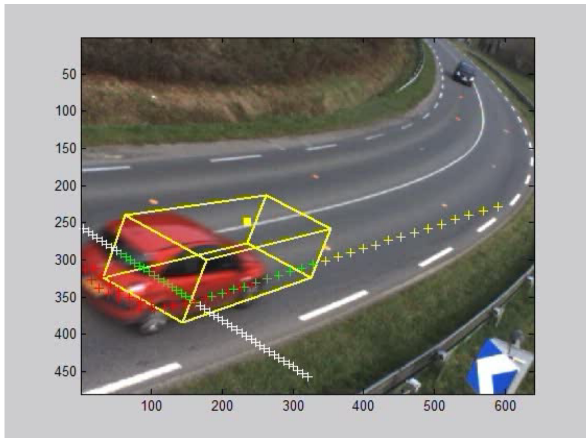
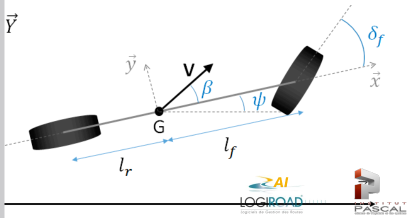
Why is Visual Tracking difficult? (Kinematic modelling)



State Vector:

- 2D position on the ground plane
- 2D motion vector on the ground plane
- Steering angle
- Acceleration



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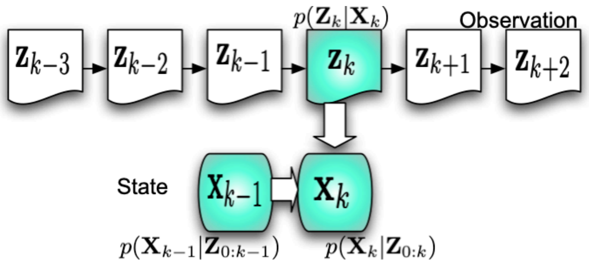
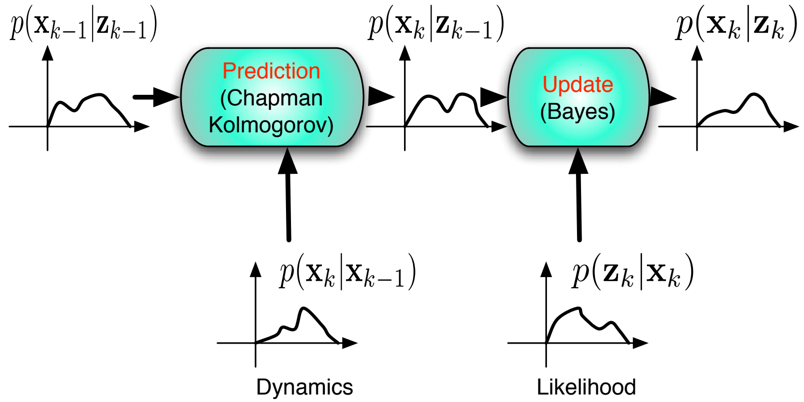
The classical (probabilistic) view of tracking



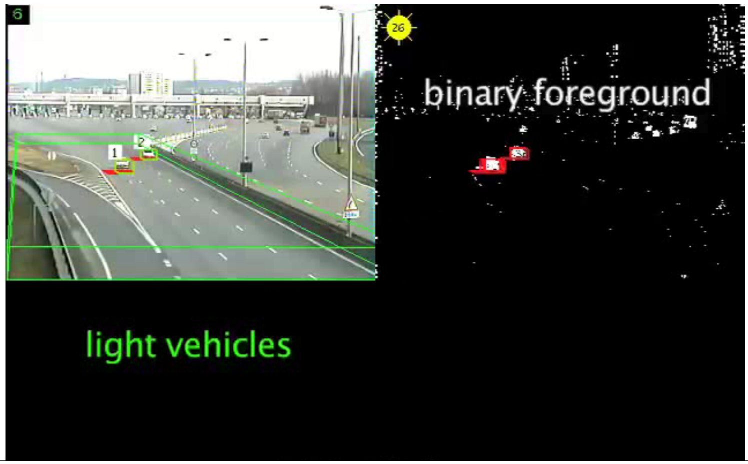
Deep Learning for Visual Tracking

The classical (probabilistic) view of tracking



Deep Learning for Visual Tracking

The classical (probabilistic) view of tracking



Deep Learning for Visual Tracking

The classical (optimisation) view of tracking

State

The State vector is an unknown parameter vector which can be estimated using optimisation techniques :

$$\hat{\mathbf{x}}_k = \arg\min_{\mathbf{x}_k \in \mathcal{X}} \mathcal{E}(\mathbf{x}_k, \mathbf{z}_k)$$

The search space $\mathcal{X}$ is often reduced using priors on motion and previous estimation.

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The classical (optimisation) view of tracking (Meanshift)

Deep Learning for Visual Tracking

Overview of Visual tracking

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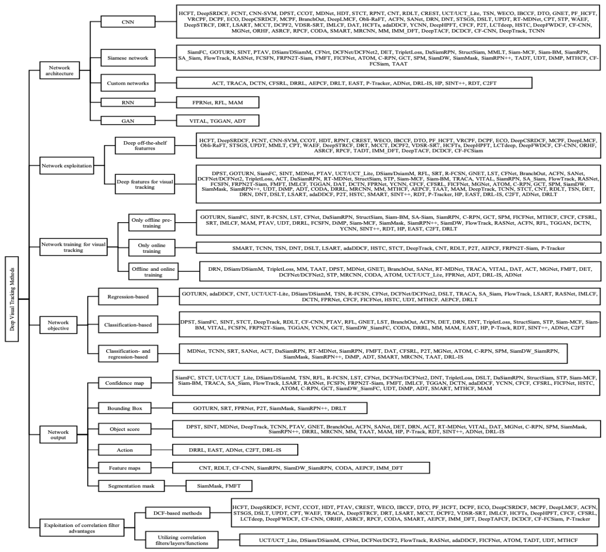
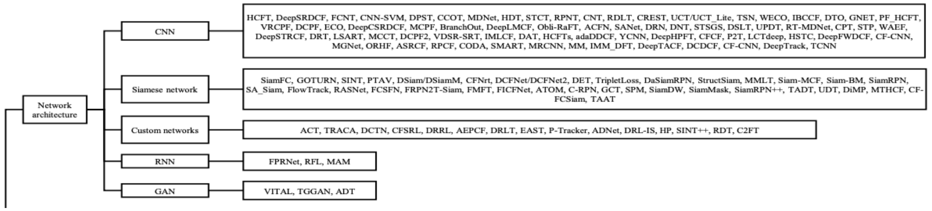
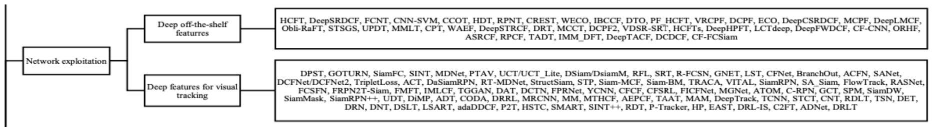


Deep Learning for Visual Tracking



Deep Learning for Visual Tracking



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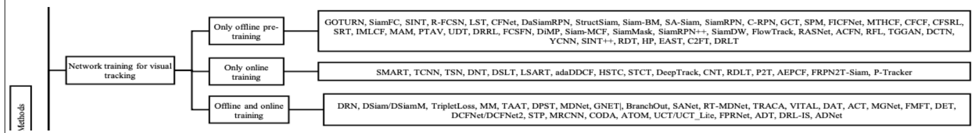

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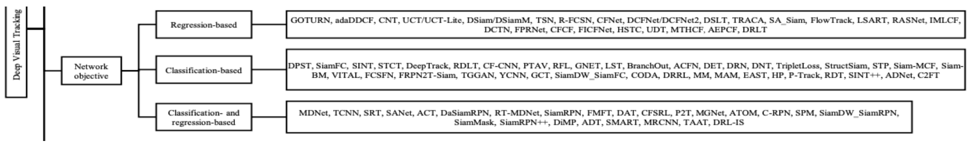

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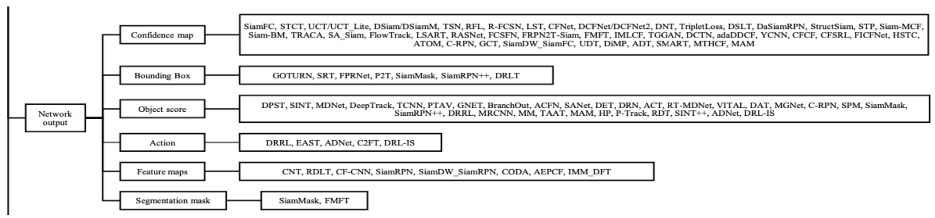

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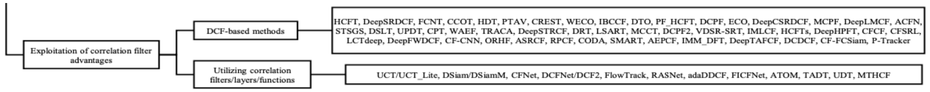

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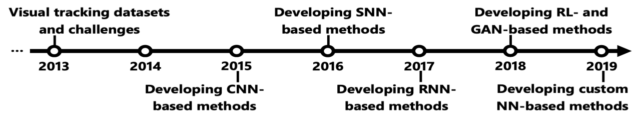

Recent history of Visual tracking

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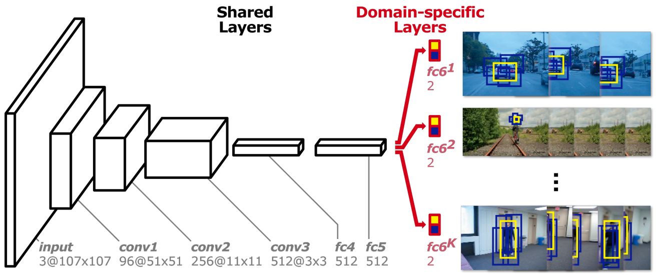
Deep Learning for Visual Tracking

CNN based model: MDNet (Multiple Domain)



Learning Multi-Domain Convolutional Neural Networks for Visual Tracking

Hyeonseob Nam
Bohyung Han
POSTECH
The Winner of The VOT2015 Challenge

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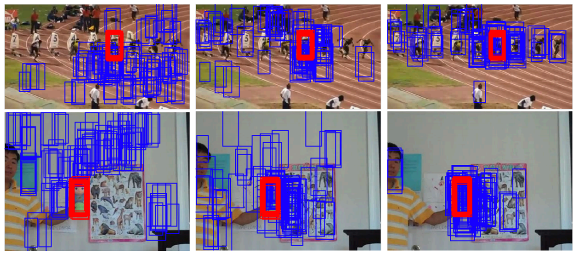
Deep Learning for Visual Tracking

CNN based model: MDNet (Multiple Domain)

Selected the domain branch and fine-tuning it according to the target



(a) 1^{st} minibatch (b) 5^{th} minibatch (c) 30^{th} minibatch

Learning Multi-Domain Convolutional Neural Networks for Visual Tracking

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POSTECH
The Winner of The VOT2015 Challenge

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Deep Learning for Visual Tracking

CNN based model: MDNet (Multiple Domain)

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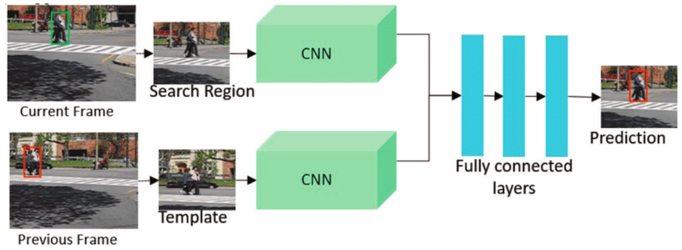
SNN based model: GOTURN

Generic Object Tracking Using Regression Networks



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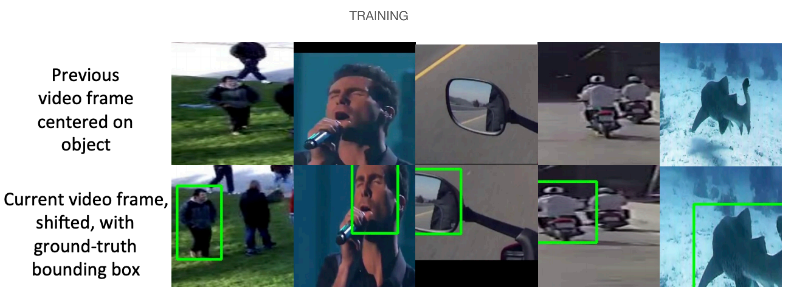
SNN based model: GOTURN

Generic Object Tracking Using Regression Networks



Held, David, Sebastian Thrun, et Silvio Savarese. « Learning to Track at 100 FPS with Deep Regression Networks ». CoRR abs/1604.01802 (2016). http://arxiv.org/abs/1604.01802.

Deep Learning for Visual Tracking

multi-object tracking

Based on Tracking-by-detection

1) Object detection
2) Metric estimation between detected objects and targets (set of objects with the same identity)
3) Association between object and target
4) target birth, death and loss.

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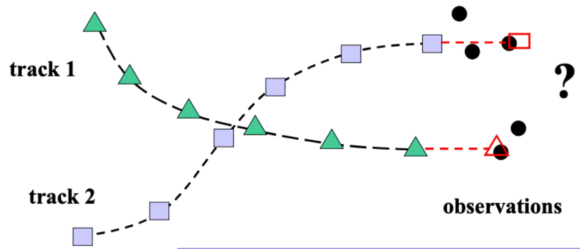
multi-object tracking

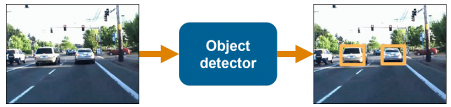
Intuition: predict next position along each track.



How to determine which observations to add to which track?

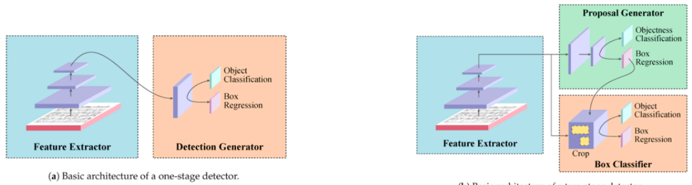
Deep Learning for Visual Tracking

Object detection networks



Two main object detector structures exist:

- One-Stage Detectors
- Two-Stage Detectors



(a) Basic architecture of a one-stage detector.

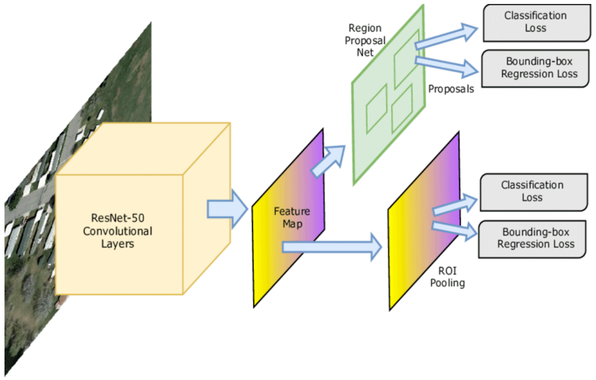
(b) Basic architecture of a two-stage detector.

Deep Learning for Visual Tracking

Object detection networks

Example of two-stages-detector: Faster-Rcnn

Ren, Shaoqing, Kaiming He, Ross Girshick, et Jian Sun. « Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks ». In *Advances in Neural Information Processing Systems 28*, édité par C. Cortes, N. D. Lawrence, D. D. Lee, M. Sugiyama, et R. Garnett, 91‑99. Curran Associates, Inc., 2015. http://papers.nips.cc/paper/5638-faster-r-cnn-towards-real-time-object-detection-with-region-proposal-networks.pdf.



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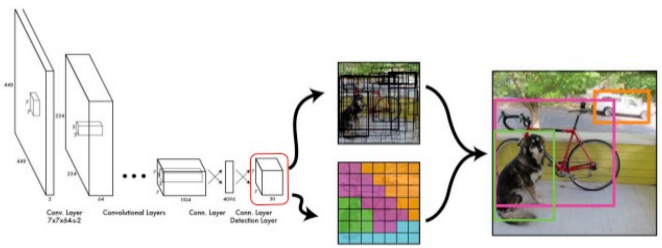
Object detection networks

Example of one-stage-detector: YOLO

YOLO: You Only Look Once



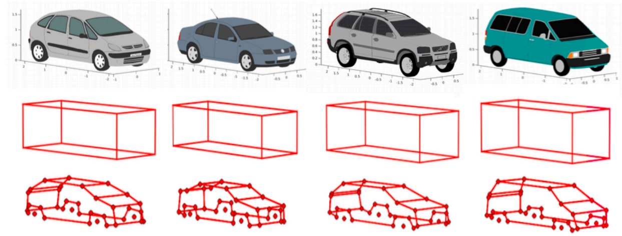
Redmon, Joseph, Santosh Divvala, Ross Girshick, et Ali Farhadi. « You Only Look Once: Unified, Real-Time Object Detection ». In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2016.

Deep Learning for 3D vehicle understanding from monocular images: toward many-task networks

System Outputs

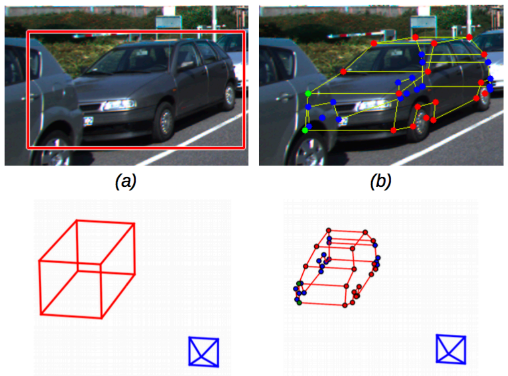
Deep Learning for 3D vehicle understanding from monocular images: toward many-task networks

3D samples of shape and template dataset



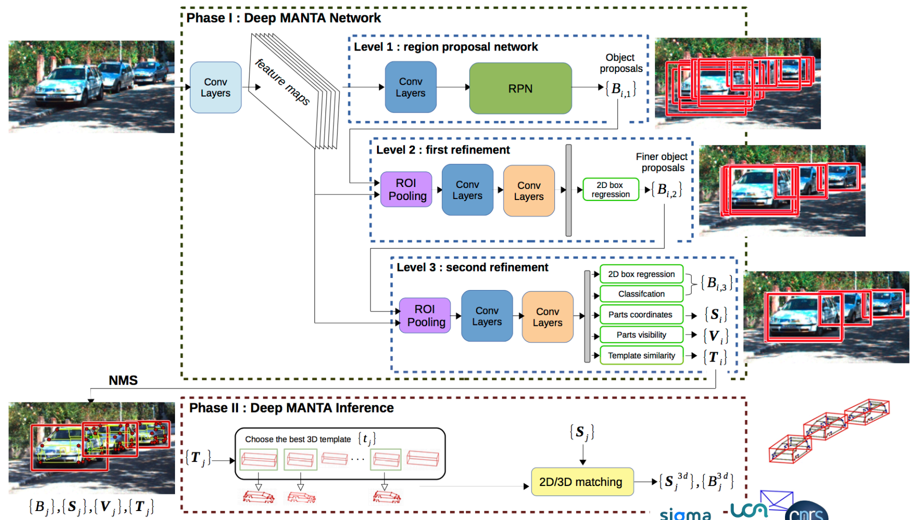
Deep Learning for 3D vehicle understanding from monocular images: toward many-task networks

Bounding box and part detection (with visibility estimation, green and blue)



(a) (b)

(c) (d)



Deep Learning for 3D vehicle understanding from monocular images

Loss functions

RPN Loss

Detection loss

Parts Loss

Visibility Loss

Template similarity loss

$$\mathcal{L} = \mathcal{L}^1 + \mathcal{L}^2 + \mathcal{L}^3$$

with

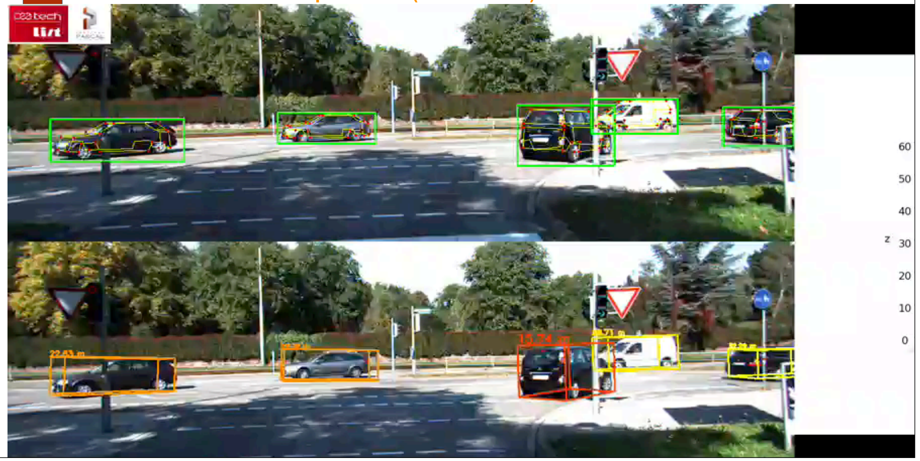
$$\mathcal{L}^1 = \mathcal{L}_{rpn},$$

$$\mathcal{L}^2 = \sum_i \mathcal{L}^2_{det}(i) + \mathcal{L}^2_{parts}(i),$$

$$\mathcal{L}^3 = \sum_i \mathcal{L}^3_{det}(i) + \mathcal{L}^3_{parts}(i) + \mathcal{L}_{vis}(i) + \mathcal{L}_{temp}(i),$$

Deep Learning for 3D vehicle understanding from monocular images

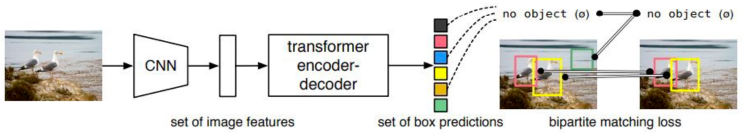
Experiments (Kitti Dataset)



Deep Learning for Visual Tracking

Object detection networks

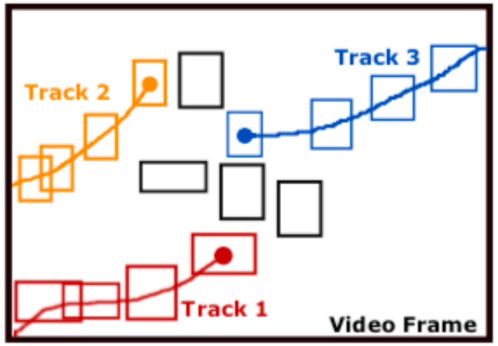
2020: Using Transformers for object detection



Carion, Nicolas, Francisco Massa, Gabriel Synnaeve, Nicolas Usunier, Alexander Kirillov, et Sergey Zagoruyko. *End-to-End Object Detection with Transformers*, 2020.

Deep Learning for Visual Tracking

Association: define metric and match objects and targets



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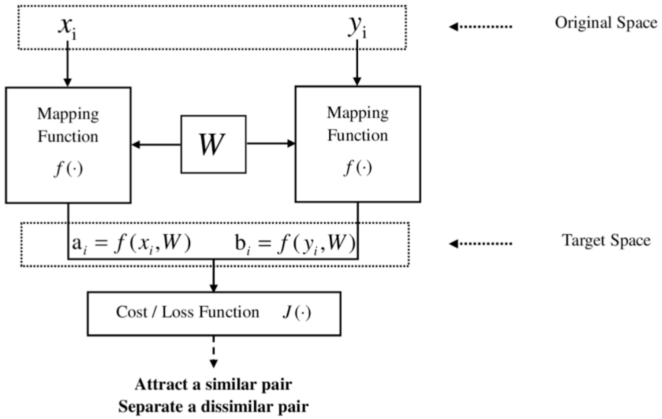
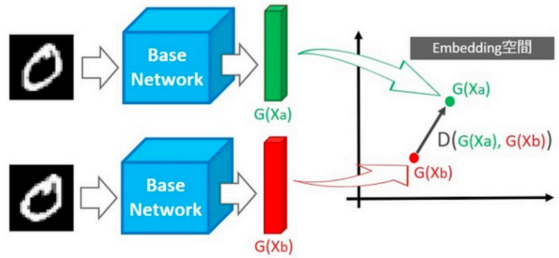
Association: define metric



Deep Learning for Visual Tracking

Association: define metric

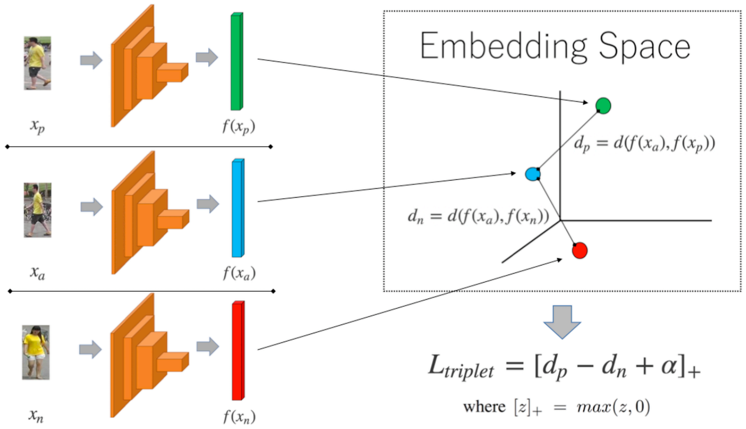


Y=0, same category, minimize Dw

$$L = \boxed{(1-Y)\frac{1}{2}(D_W)^2} + \boxed{(Y)\frac{1}{2}\{max(0, m - D_W)\}^2}$$

Y=1, different category, maximize Dw to m

Deep Learning for Visual Tracking



$$L_{triplet} = [d_p - d_n + \alpha]_+$$

where $[z]_+ = max(z, 0)$

Association: define metric

Deep Learning for Visual Tracking

Association: define metric and match objects and targets (association matrix)

We have N objects in previous frame and M objects in current frame. We can build a table of match scores m(i,j) for i=1…N and j=1…M. For now, assume M=N.

	1	2	3	4	5
1	0.95	0.76	0.62	0.41	0.06
2	0.23	0.46	0.79	0.94	0.35
3	0.61	0.02	0.92	0.92	0.81
4	0.49	0.82	0.74	0.41	0.01
5	0.89	0.44	0.18	0.89	0.14

problem: choose a 1-1 correspondence that maximizes sum of match scores.

Deep Learning for Visual Tracking

Association: define metric and match objects and targets (association matrix)

5x5 matrix of match scores

0.95	0.76	0.62	0.41	0.06
0.23	0.46	0.79	0.94	0.35
0.61	0.02	0.92	0.92	0.81
0.49	0.82	0.74	0.41	0.01
0.89	0.44	0.18	0.89	0.14

working from left to right, choose one number from each column, making sure you don't choose a number from a row that already has a number chosen in it.

How many ways can we do this?

5 x 4 x 3 x 2 x 1 = 120 (N factorial)

Deep Learning for Visual Tracking

Association: define metric and match objects and targets (association matrix)

$$\begin{array}{ccccc} \boxed{0.95} & 0.76 & 0.62 & 0.41 & 0.06 \\ 0.23 & \boxed{0.46} & 0.79 & 0.94 & 0.35 \\ 0.61 & 0.02 & \boxed{0.92} & 0.92 & 0.81 \\ 0.49 & 0.82 & 0.74 & \boxed{0.41} & 0.01 \\ 0.89 & 0.44 & 0.18 & 0.89 & \boxed{0.14} \end{array}$$

score: 2.88

$$\begin{array}{ccccc} 0.95 & 0.76 & 0.62 & \boxed{0.41} & 0.06 \\ \boxed{0.23} & 0.46 & 0.79 & 0.94 & 0.35 \\ 0.61 & 0.02 & \boxed{0.92} & 0.92 & 0.81 \\ 0.49 & \boxed{0.82} & 0.74 & 0.41 & 0.01 \\ 0.89 & 0.44 & 0.18 & 0.89 & \boxed{0.14} \end{array}$$

score: 2.52

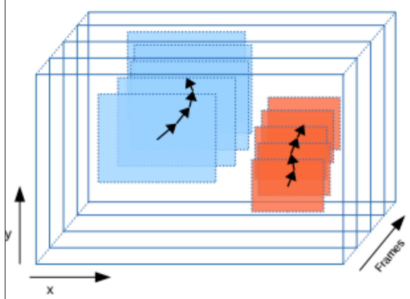
$$\begin{array}{ccccc} 0.95 & \boxed{0.76} & 0.62 & 0.41 & 0.06 \\ 0.23 & 0.46 & 0.79 & \boxed{0.94} & 0.35 \\ 0.61 & 0.02 & 0.92 & 0.92 & \boxed{0.81} \\ 0.49 & 0.82 & \boxed{0.74} & 0.41 & 0.01 \\ \boxed{0.89} & 0.44 & 0.18 & 0.89 & 0.14 \end{array}$$

score: 4.14

Deep Learning for Visual Tracking

Object detection networks

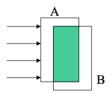
SORT: Tracking-by-detection



State Vector : Position, scale, ratio $\mathbf{x} = [u, v, s, r, \dot{u}, \dot{v}, \dot{s}]^T,$

Trajectory prediction: Kalman filter

Association: IOU distance and Hungarian Algorithm



$$\text{score} = \frac{2 * \text{area(A and B)}}{\text{area(A)} + \text{area(B)}}$$

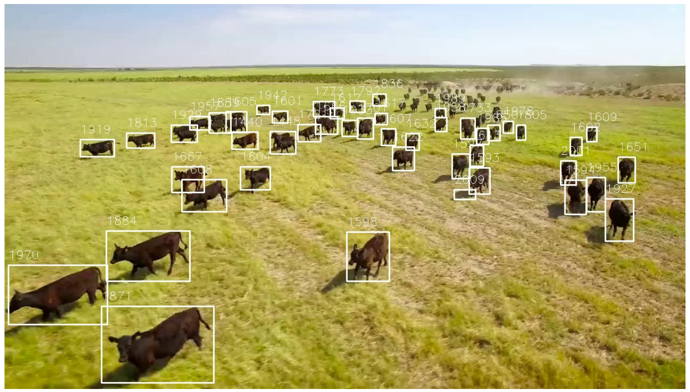
Detections (columns), Traj (rows)

a1	a2	a3	a4
b1	b2	b3	b4
c1	c2	c3	c4
d1	d2	d3	d4

Bewley, Alex, ZongYuan Ge, Lionel Ott, Fabio Ramos, et Ben Upcroft. « Simple Online and Realtime Tracking ». *CoRR* abs/1602.00763 (2016). http://arxiv.org/abs/1602.00763.

Deep Learning for Visual Tracking

SORT: Tracking-by-detection

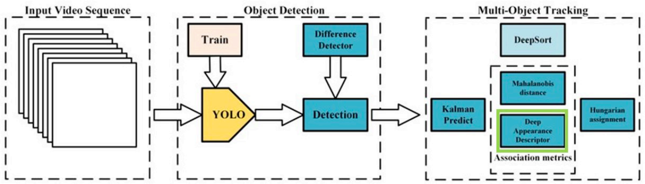


https://medium.com/neuromation-blog/tracking-cows-with-mask-r-cnn-and-sort-fcd4ad68ec4f

Deep Learning for Visual Tracking

DeepSORT: Tracking-by-detection

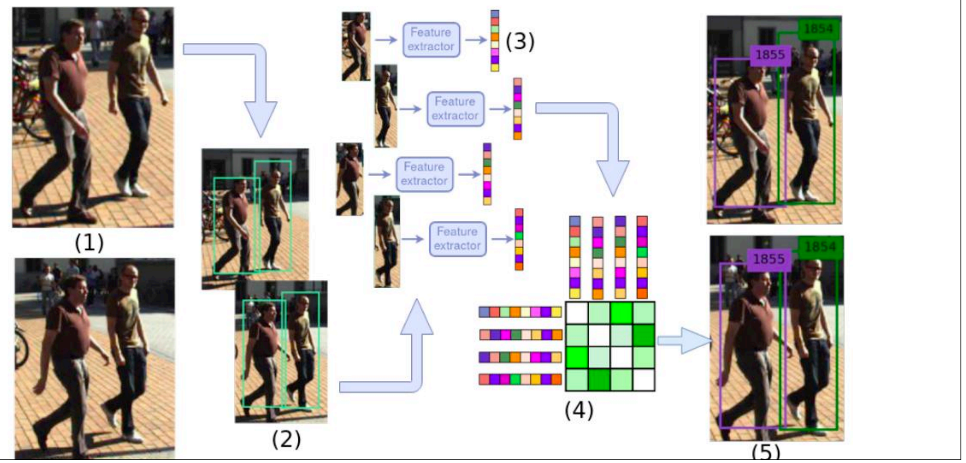
SORT WITH DEEP ASSOCIATION METRIC



https://medium.com/neuromation-blog/tracking-cows-with-mask-r-cnn-and-sort-fcd4ad68ec4f

Deep Learning for Visual Tracking

DeepSORT: Tracking-by-detection SORT WITH DEEP ASSOCIATION METRIC



Deep Learning for Visual Tracking

DeepSORT: Tracking-by-detection

SORT WITH DEEP ASSOCIATION METRIC

The power of video interlacing

Introduction

The classical tracking-by-detection scheme:

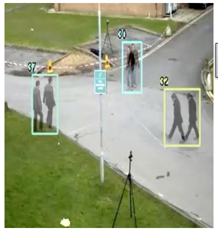
- object detection (for each frame of the video sequence)
- **association (spatio-temporal and/or appearance models)**
- birth and death trajectories algorithms

Institut Pascal

The power of video interlacing

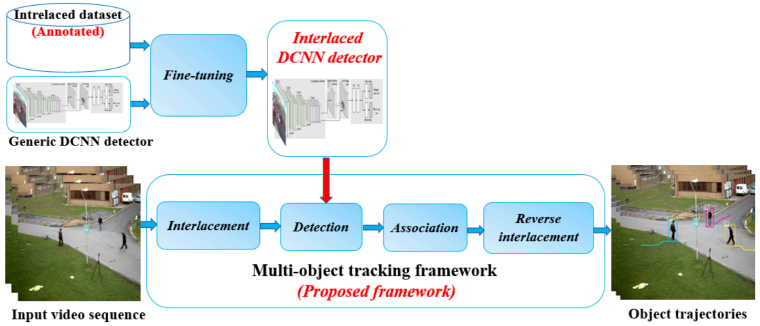
The key idea

build an **interlaced** video and train an interlaced pedestrian detector



to:
- increase overlapping between successive frames
- learn appearance association within a deep convolution neural network

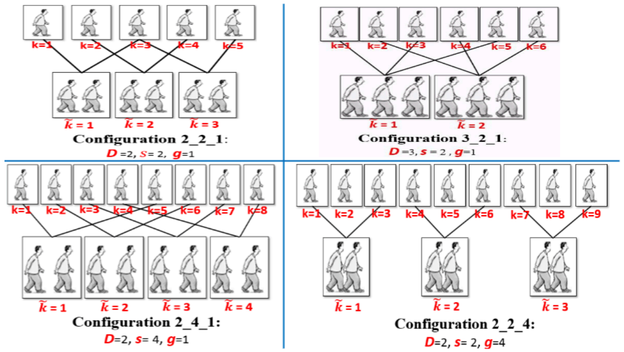
The power of video interlacing



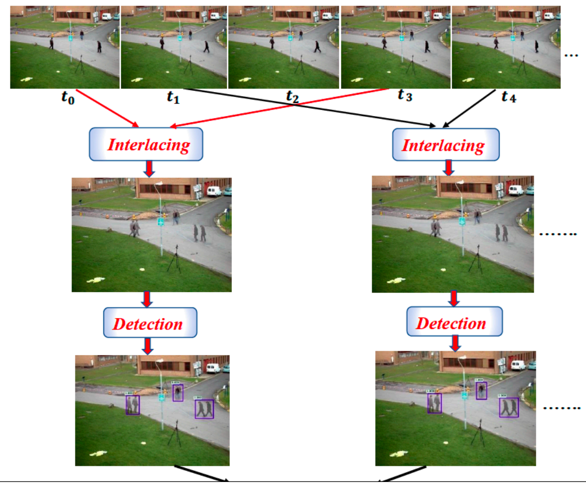
The power of video interlacing

Build a interlaced video

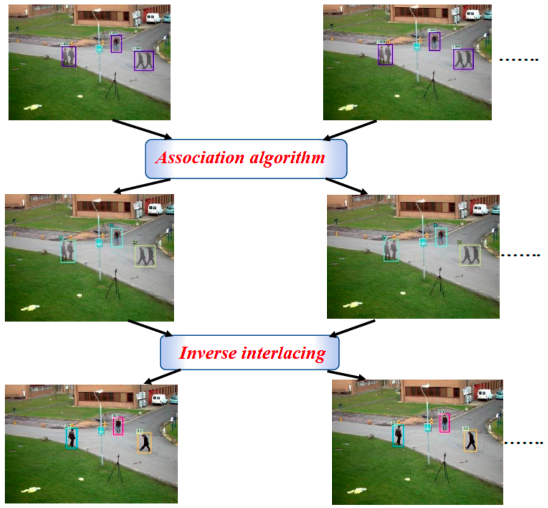
$$\tilde{I}_{\tilde{k}}(x,y) \doteq \sum_{d=0,\ldots,(D-1)} I_{(\tilde{k}g+ds)}(x,y).\delta(y[D]-d)$$



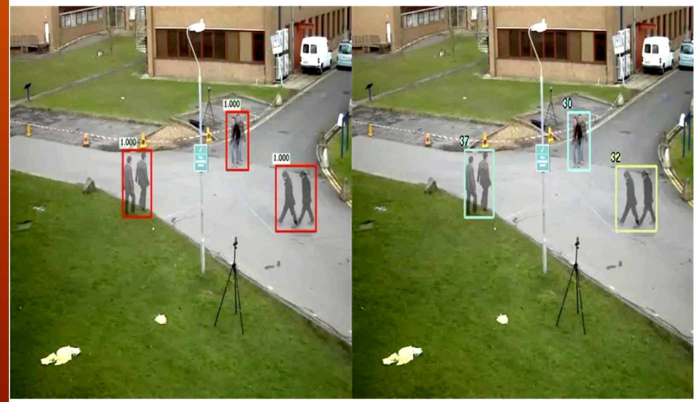
The power of video interlacing



The power of video interlacing



The power of video interlacing



Detection Tracking

Institut Pascal

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