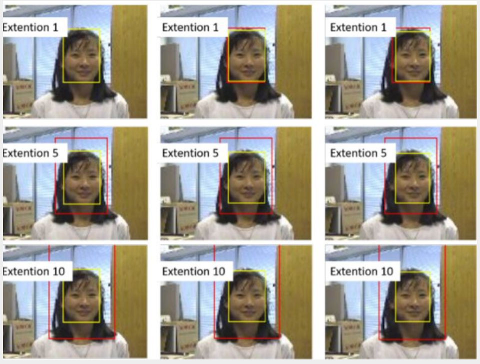
Model Decay in Long-Term Tracking

Efstratios Gavves[1], Ran Tao[2], Deepak K. Gupta [1]and Arnold Smeulders[1]
[1]QUVA Lab, University of Amsterdam, The Netherlands
[2]Kepler Vision Technologies
Email: D.K.Gupta@uva.nl
Paper Id: 839

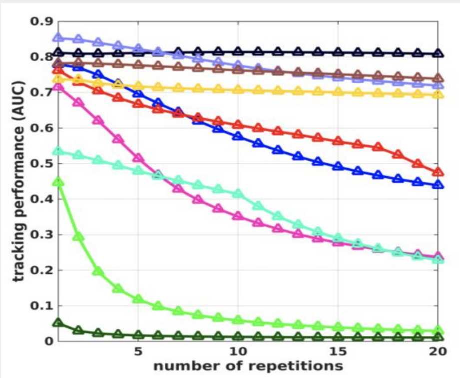
UNIVERSITEIT VAN AMSTERDAM

Introduction

Small error in tracker prediction can accumulate over a large number of frames to eventually cause model drift.



Example from OTB100 showing 3 frames from 3 different repetitions. Note that the predictions in the similar frames worsens over longer durations due to model decay.



AUC scores for ECO tracker on multiple repetitions of 10 videos from OTB100 showing model decay.

Mathematical representation of model decay

Popular learning strategy for trackers:

$$\phi_{t+1} = \arg\min_{\phi} \mathcal{L}(x_{1:t}, y_{1:t}) \qquad y_{t+1} = f(x_{t+1}; \phi_{t+1})$$

where f is the ϕ parameterized tracker that minimizes the tracker loss $\mathcal{L}$ over the dataset $D = [x_{1:t}, y_{1:t}]$

Assuming Gaussian noise with variance σ_i^2 we can state:

$$y_i = y_i^* + \delta_i, \ \text{and} \ \delta_i \sim N(0, \sigma_i^2)$$

Model update can be represented as:

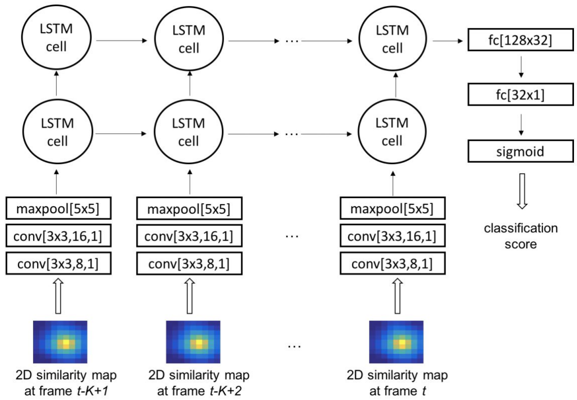
$$\phi_{t+1} - \phi_t = \underbrace{-2\eta\mathbb{E}[(f_{i,t} - y_i^*) \cdot \nabla_\phi f_{i,t}]}_{\text{Perfect parameter update}} + \underbrace{2\eta\mathbb{E}[\delta_i \cdot \nabla_\phi f_{i,t}]}_{\text{Parameter bias}}$$

Decay recognition network

Tracker drift can be reduced by avoiding random model updates caused due to wrong predictions that are very similar to the original target.

It is important that every update is made cautiously.

For selecting the frames to update the tracker model, we use an LSTM-based module referred as decay recognition network.



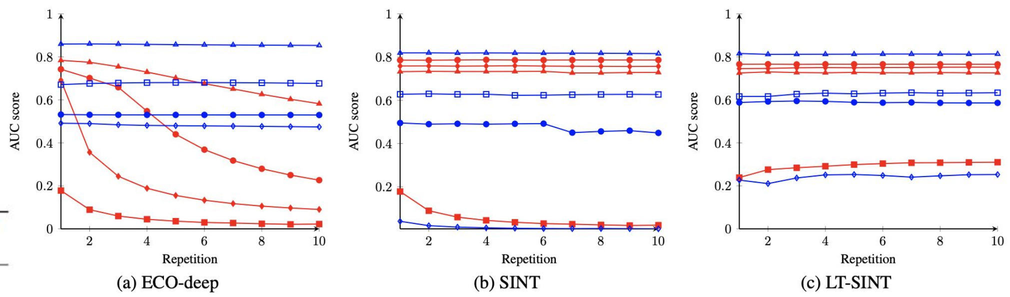
Network architecture for decay recognition network. Based on K-1 previous evaluations, it decides whether the current prediction can be used to update the model.

Experiments

Our LT-SINT variant, equipped with the decay recognition network, tackles model decay well and performs well for long-term tracking.

	UAV20L	YouTube Long	YouTube Long *(20 sec)*	OxUvA
ECO-DEEP [4]	42.7	7.1	1.4	39.5
TLD [14]	22.8	22.4	20.2	20.8
LTCT [21]	25.5	2.2	0.2	29.2
SPL [31]	35.6	—	—	—
SRDCF [7]	34.3	—	—	—
MUSTer [13]	32.9	—	—	—
SiamFC+R [33]	—	—	—	42.7
SiamFC [34]	—	—	—	39.1
MDNet [27]	—	—	—	47.2
SINT [32]	49.4	37.6	—	42.6
EBT [37]	—	—	—	32.1
BACF [10]	—	—	—	31.6
Staple [1]	—	—	—	27.3
LT-SINT	**52.4**	**42.1**	**39.5**	**57.9**

Performance comparison of LT-SINT with other trackers on long videos.



Comparison of AUC scores for three different trackers. Here LT-SINT is equipped with the decay recognition network.

Conclusions

- Too many model updates can lead to tracker drift in long videos.
- To avoid model drift, cautious updates should be performed.
- The weak temporal correspondence used by the deay recognition network helps to tackle model decay.