Staple: Complementary Learners for Real-Time Tracking

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Code available!

github.com/bertinetto/staple

Model-free, short-term, single-target tracking

Problem: track an arbitrary object selected online.

- Sole supervision: bounding box at first frame.
- *Model-free*: agnostic to the object's class.
- *Short-term*: no re-detection logic.

Main challenges

- Large variability of target objects and video scenarios.
- *Stability-Plasticity* dilemma.

Related work

Correlation filters

- Dense sampling of object and background.
- Fast evaluation: sampling space is a circulant matrix and can be diagonalized with DFT.

from [Henriques12]

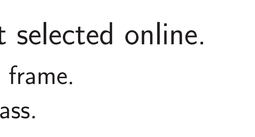
Colour histograms

- Dense sampling of object and background.
- Fast evaluation with Integral Images.

from [Possegger15]

Deep trackers

- Benefit from expressiveness of conv-net features.
- Require to perform fine-tuning online: slow (far from real-time).

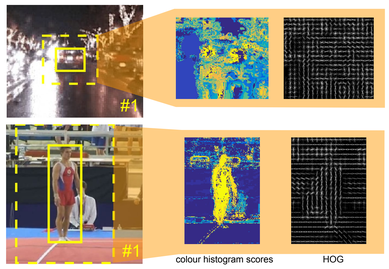


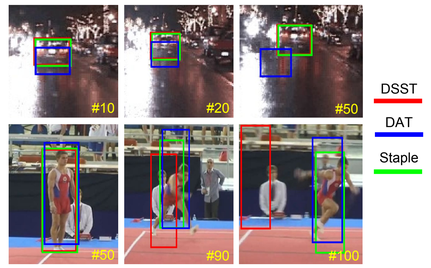
from [Nam15]

Ensemble methods

- Run many trackers in parallel, modelling individual confidences.
- Merge final estimations only. (*e.g.* [Kwon11], [Wang14], [Zhanh14])

Motivation





- Colour distributions rely on pixel values to discriminate target from background→no concept of locality: robust to shape changes, sensitive to blur and poor illumination.
- Template models rely on spatial configuration →robust to blur and poor illumination, sensitive to shape changes.

Formulation

Staple = **S**um of **T**emplate **a**nd **P**ixel-wise **Le**arners.

- Combination of score functions f_{tmpl} and f_{hist} evaluated on complementary cues

$$f(x) = \gamma_{\text{tmpl}} f_{\text{tmpl}}(x) + \gamma_{\text{hist}} f_{\text{hist}}(x)$$

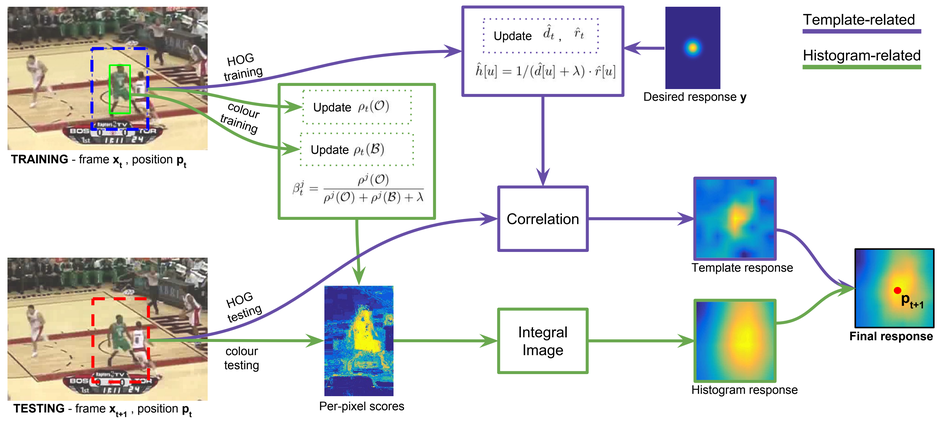
- $f_{\text{tmpl}}(x; h)$: linear function of HOG feature image ϕ_x.
- $f_{\text{hist}}(x; \beta)$: average of a score image computed from the histogram model β.
- Two ridge regression problems at each t depending on previous images/locations $\mathcal{X}_t$:

$$h_t = \arg\min_h \left\{ L_{\text{tmpl}}(h; \mathcal{X}_t) + \tfrac{1}{2}\lambda_{\text{tmpl}} \|h\|^2 \right\}$$

$$\beta_t = \arg\min_\beta \left\{ L_{\text{hist}}(\beta; \mathcal{X}_t) + \tfrac{1}{2}\lambda_{\text{hist}} \|\beta\|^2 \right\}$$

- Correlation (in Fourier domain) and Integral Image→dense responses with fast sliding window search.

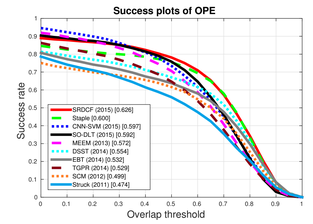
Pipeline

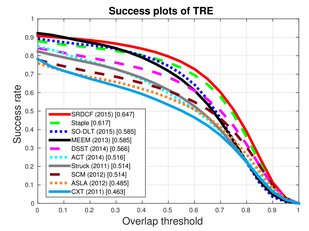


Results

Despite its extreme simplicity, **Staple outperforms the state-of-the-art** on multiple benchmarks, yet running at **80 fps**.

OTB-13

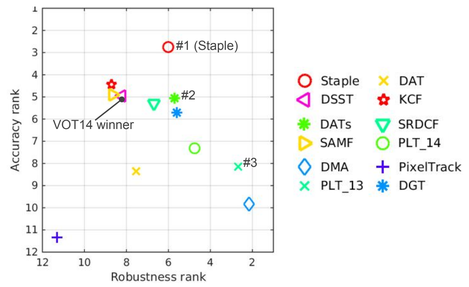




VOT 2014

Tracker	Year	Where	Accuracy	# Failures	Overall Rank	Speed (fps)
Staple	2016	CVPR	0.644	9.38	4.37	80
DATs	2015	CVPR	0.580	13.17	5.39	15
PLT_13	2013	VOT	0.523	1.66	5.41	76
DGT	2014	TIP	0.534	13.78	5.66	10
SRDCF	2015	ICCV	0.600	15.90	5.99	5
DMA	2015	CVPR	0.476	0.72	6.00	8
PLT_14	2014	VOT	0.537	3.41	6.03	63
KCF	2015	PAMI	0.613	19.79	6.58	80
DSST	2014	BMVC	0.607	16.90	6.59	24
SAMF	2014	ECCVw	0.603	19.23	6.79	7
DAT	2015	CVPR	0.519	15.87	7.95	17
PixelTrack	2013	ICCV	0.420	22.58	11.31	**114**

Table 1 : Recent trackers on the VOT14 benchmark.



VOT 2015

Tracker	Year	Where	Accuracy	# Failures	Rank	Speed (fps)
MDNet	2015	ICCV	0.583	0.69	14.31	1
DeepSRDCF	2015	VOT	0.528	1.05	19.16	< 1
SRDCF	2015	ICCV	0.521	1.24	21.01	5
Staple	2016	CVPR	0.533	1.39	21.64	**80**
SO-DLT	2015	arXiv	0.535	1.78	22.71	5
NSAMF	2015	VOT	0.490	1.29	22.93	5
EBT	2015	arXiv	0.453	1.02	23.01	5
sPST	2015	ICCV	0.508	1.48	23.04	2
RAJSSC	2015	VOT	0.518	1.63	23.53	2
SC-EBT	2015	ICML	0.523	1.86	23.70	-

Table 2 : VOT15 top 10 (of 63)

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www.robots.ox.ac.uk/~luca/staple.html