FAST ROBUST TRACKING VIA DOUBLE CORRELATION FILTER FORMULATION

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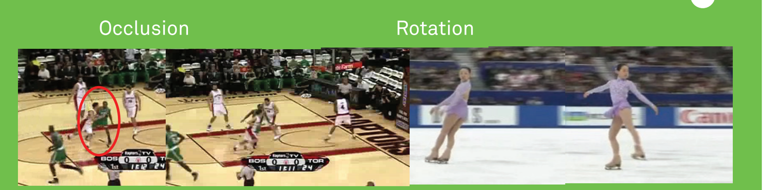
Object tracking

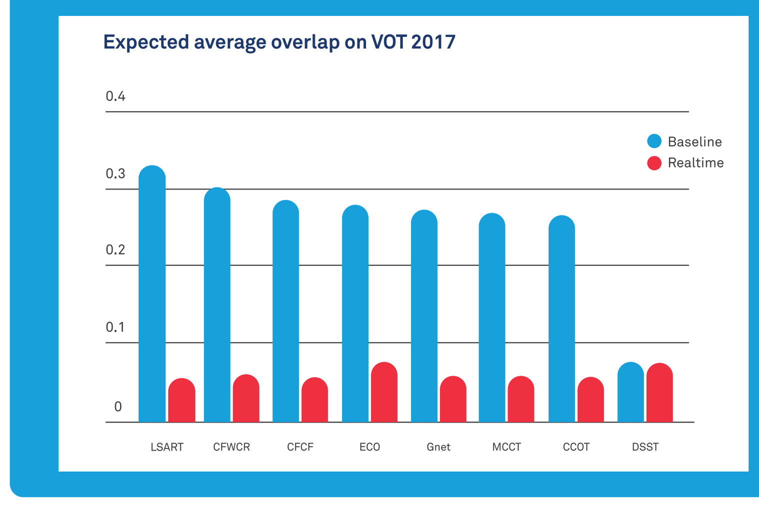
- The objective is to track a single object through a sequence of frames, given its position in the first frame
- Representation of the object is learned from the first frame and this representation is iteratively updated with information from the subsequent frames
- This representation is used to detect the object in the next frame, these detections are then used for update

Challenges in tracking



- Illumination variation, Scale variation, Deformation, Fast Motion, Viewpoint change, Out of View, Background Clutter, Low Resolution
- Prior information about the object appearance (as used in trackers utilizing deep features) or trajectory can also help

Deep learning trackers



- Simple correlation filter based trackers (like DSST) outperform Deep Learning trackers on higher frame rate (240FPS) videos on all the challenges in tracking except non-rigid deformation

MOSSE and KCF

- Using a simple template based correlation filter to detect the object is not sufficient. The correlation filter has to be trained specifically to discriminate the object from the background and this training must be done online. Bolme et. al. solve this problem through the Minimum Output Sum of Squared Error (MOSSE) tracker

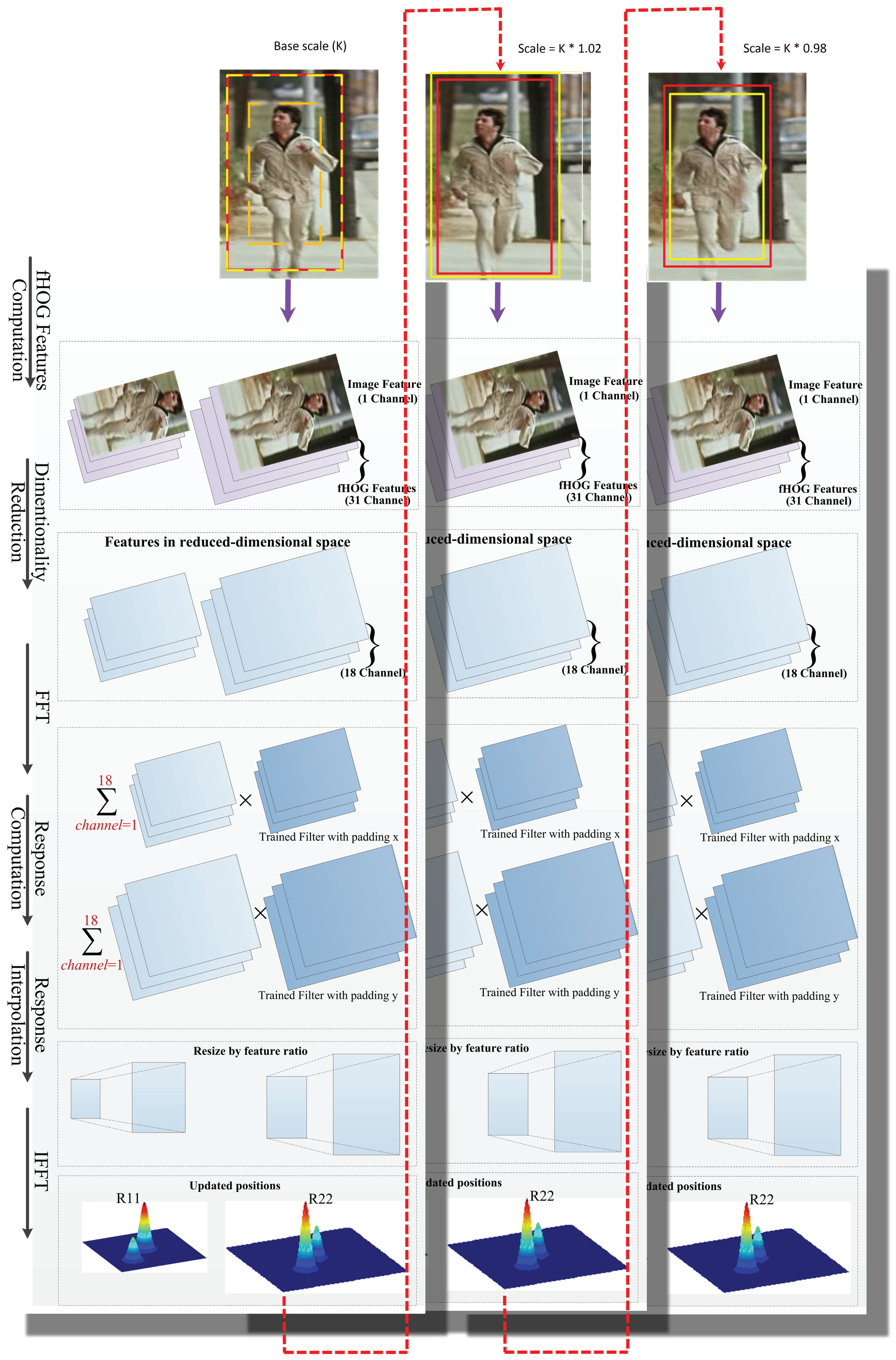
$$H_i^* = \frac{A_i = \eta G_i \circledast F_i^* + (1-\eta)A_{i-1}}{(B_i = \eta F_i \circledast F_i^* + (1-\eta)B_{i-1}) + \lambda}$$

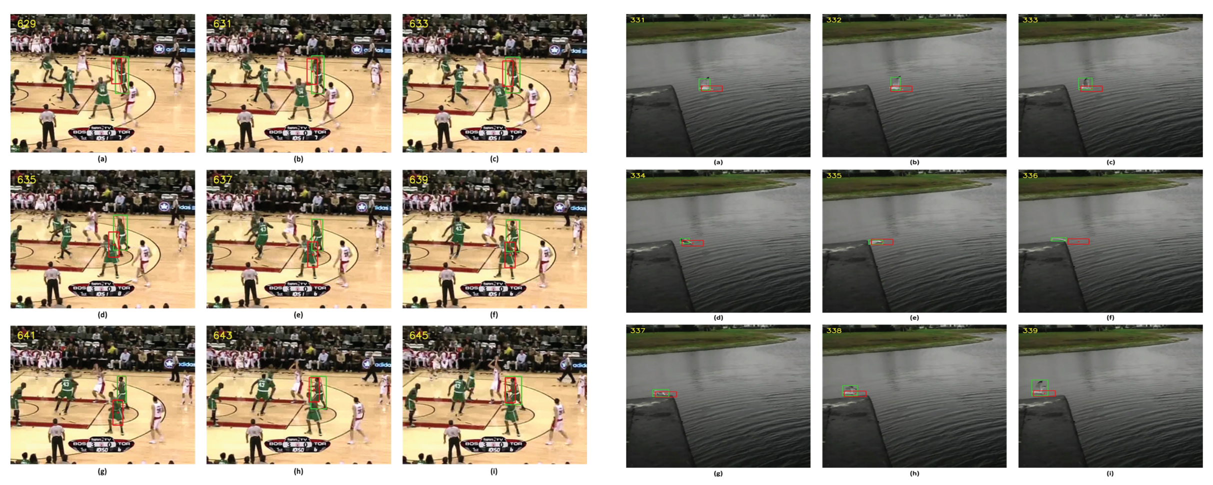
- Henriques et al. generalized this further by incorporating the Kernel Trick, producing a kernelized Correlation Filter using Gaussian, linear, polynomial and RBF kernels.

DSST and fDSST

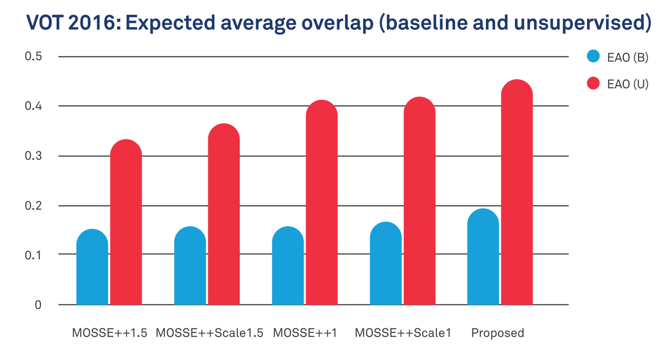
- In Discriminative Scale Space Tracking (DSST), Danelljan et al. extend the KCF approach to tracking in the scale space by using a separate scale filter and also use fHoG features. In fast DSST, Danelljan et al. introduced the idea of using PCA to reduce the dimensionality of the filter leading to faster filter response computation and update
- Features like Color names or Deep Neural Network Features are also complimentary to these approaches and can further improve results
- We propose yet another complementary approach that provides significant gains in performance on the VOT 2016 and 2017 benchmarks

Methodology

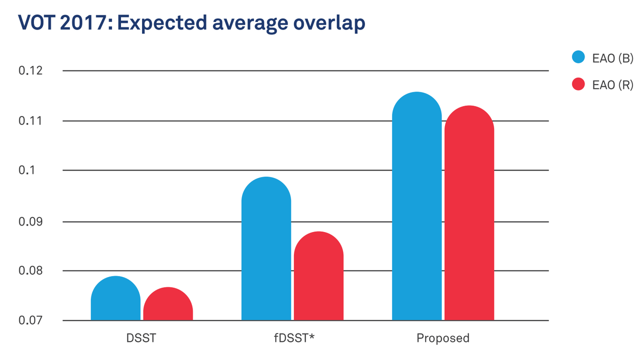




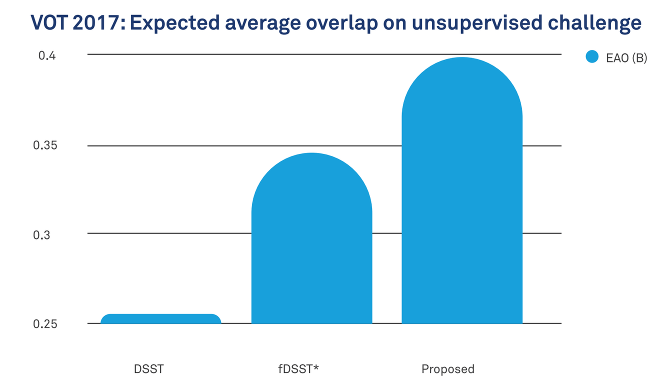
Experimental results



Performance comparison with trackers having different padding size with and without scale estimation on VOT 2016



Performance comparison with DSST and fDSST on VOT 2017



Performance comparison with DSST and fDSST on VOT 2017 Unsupervised Challenge

Tracker	R	A	EAO (B)	EFO
KCF2014	1.95	0.48	0.192	21.79
SAMF2014	1.91	0.50	0.186	4.01
DSST2014	2.38	0.52	0.181	12.75
ART_DSST	2.51	0.50	0.167	8.45
sKCF	2.86	0.48	0.153	91.06
fDSST*	2.64	0.49	0.164	13.02
Proposed	2.03	0.48	0.195	42.51

Performance comparison with other correlation based trackers submitted in VOT 2016

Conclusion

We have proposed a new method to track objects using multiple correlation filters. This method enables real-time tracking and corrects past errors. This is done by combining the information from multiple trackers in the light of newer frames. The traditional scale handling approach has also been expedited. VOT 2016 and 2017 benchmarks have evaluated this method and have found significant improvements in speed and performance.

References

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