Efficient correlation filter tracking with adaptive training sample update scheme

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Abstract

Visual tracking serves as a significant module in many applications. However, the heavy computation and low speed of many recent trackers restrict their applications in some computing power restricted scenarios. On the other hand, the simple update scheme of most correlation filter based trackers limits their robustness during target deformation and occlusion. In this paper, we explore the update scheme of correlation filter based trackers and propose an efficient and adaptive training sample update scheme. Training sample extracted in each frame is updated to the training set according to its distance between existing samples measured with difference hashing algorithm(DHA) or discarded according to tracking result reliability. Experiments on **OTB-2015**, **Temple Color 128** and **UAV123** demonstrate our tracker performs favourably against state-of-the-art trackers with light computation and runs over **100 fps** on desktop computer with Intel i7-8700 CPU(3.2GHz).

Contributions

1. We propose efficient **CRCF ATU** tracker with outstanding performance suitable for real-time applications.
2. We adaptively update training set and measure sample distance with difference hashing algorithm.
3. We extend conventional DCF to multi-training-sample formulation with better generalization ability.

Method

Multi-training-sample DCF

We incorporate multiple training samples into traditional DCF formulation

$$E(\mathbf{h}) = \sum_{k=1}^{N} \alpha_k || \sum_{d=1}^{D} \mathbf{h}_d * \mathbf{x}_{kd} - \mathbf{y}||^2 + \lambda ||\mathbf{h}||^2 \quad (1)$$

with closed-form solution in Fourier Domain as

$$\hat{\mathbf{h}}_d = \frac{\sum_{k=1}^{N} \alpha_k \hat{\mathbf{x}}_{kd}^* \odot \hat{\mathbf{g}}}{\sum_{k=1}^{N} \alpha_k \sum_{d=1}^{D} \hat{\mathbf{x}}_{kd}^* \odot \hat{\mathbf{x}}_{kd} + \lambda} \quad (2)$$

Adaptive training sample update scheme

We maintain a compact training set with generative Gaussian model and adopt **difference hashing algorithm (DHA)** to measure the distance between sample.Each sample patch is resized to 8×9 as $\mathbf{B} \in \mathbb{R}^{8\times 9}$ and the hashing matrix $\mathbf{H} \in \mathbb{R}^{8\times 8}$ is computed as

$$h_{i,j} = \begin{cases} 1, & \text{if } b_{i,j} > b_{i,j+1} \\ 0, & \text{otherwise} \end{cases} \quad (3)$$

Sample distance is measured with hashing matrics.

$$d_{lc} = \sum_{i=1}^{8} \sum_{j=1}^{8} (h_{i,j}^c \oplus h_{i,j}^l) \quad (4)$$

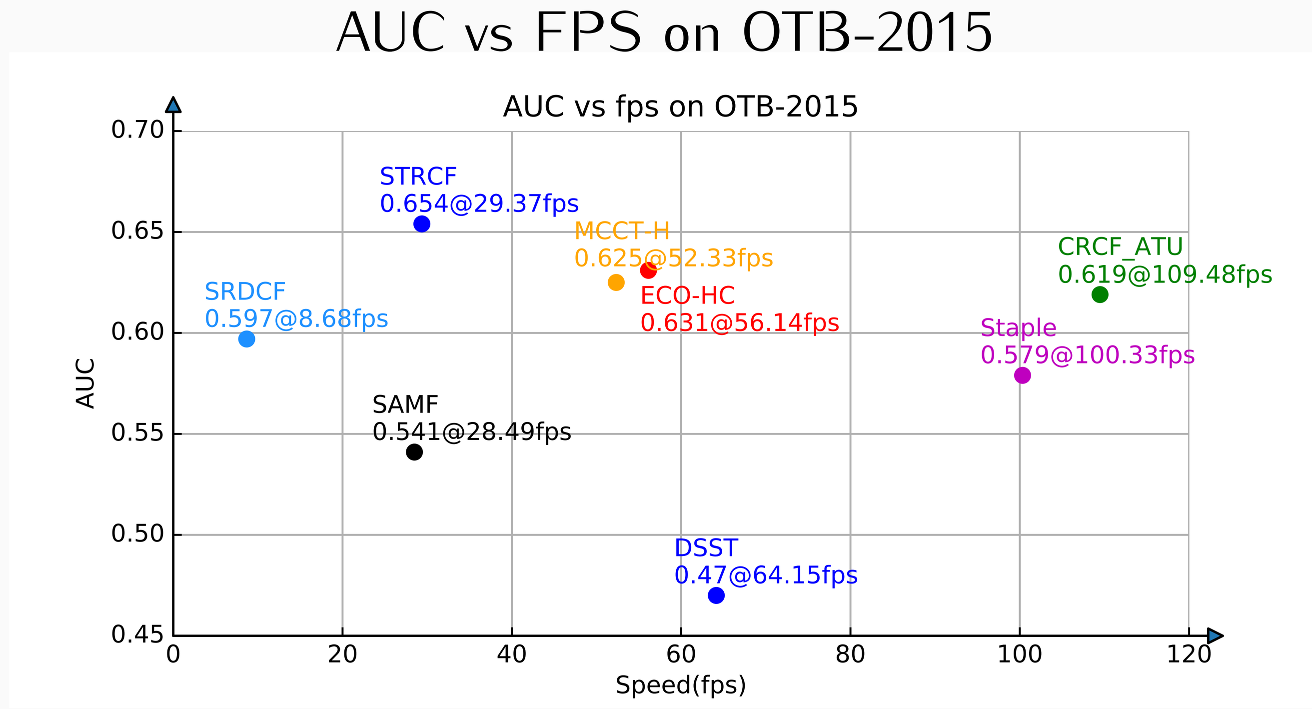
We use $\tau(R) = \max(R) APCE(R)$ to measure response map reliability. Tracking result is considered to be **unreliable** only when the reliability of **correlation filter response**, **color-based response** and **merged response** are all under a certain ratio of their corresponding historical average. Unreliable frames are not updated to training set.

$$\frac{\tau(R_{CF})}{\bar{\tau}(R_{CF})} < T_{CF}, \frac{\tau(R_{CR})}{\bar{\tau}(R_{CR})} < T_{CR}, \frac{\tau(R)}{\bar{\tau}(R)} < T_R \quad (5)$$

Experimental Results

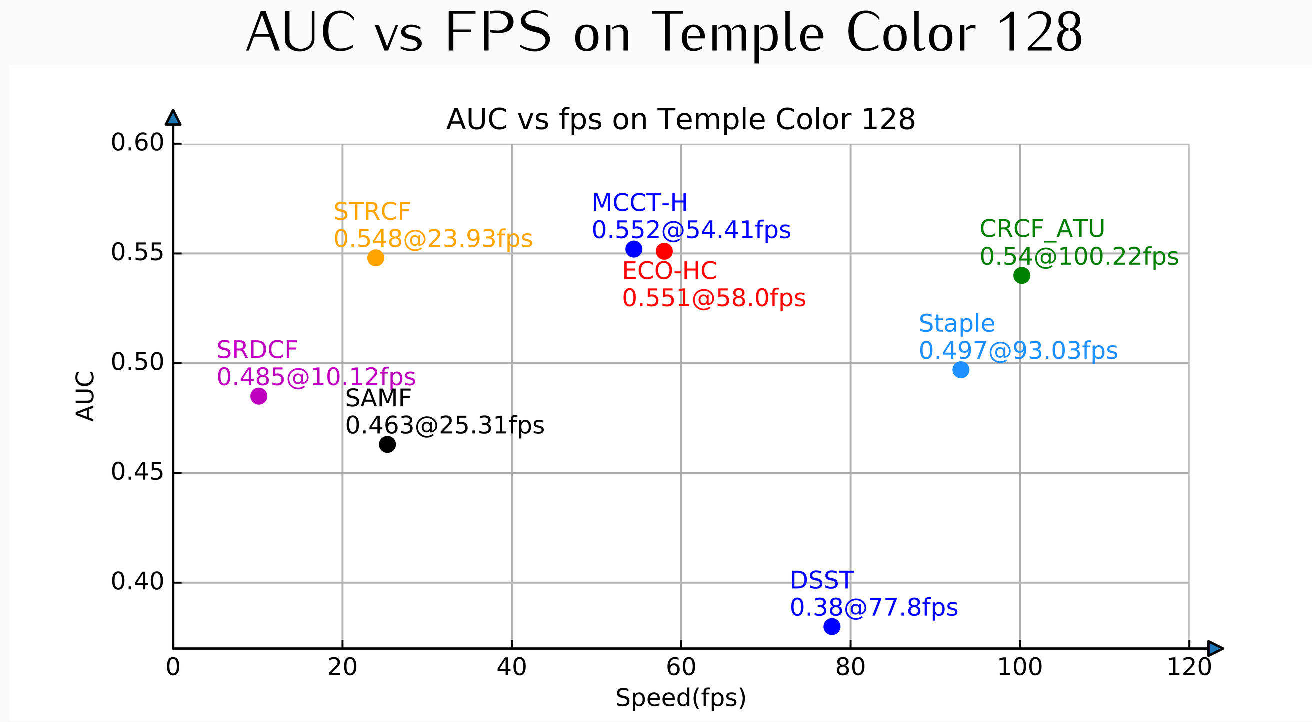
OTB-2015

AUC vs FPS on OTB-2015



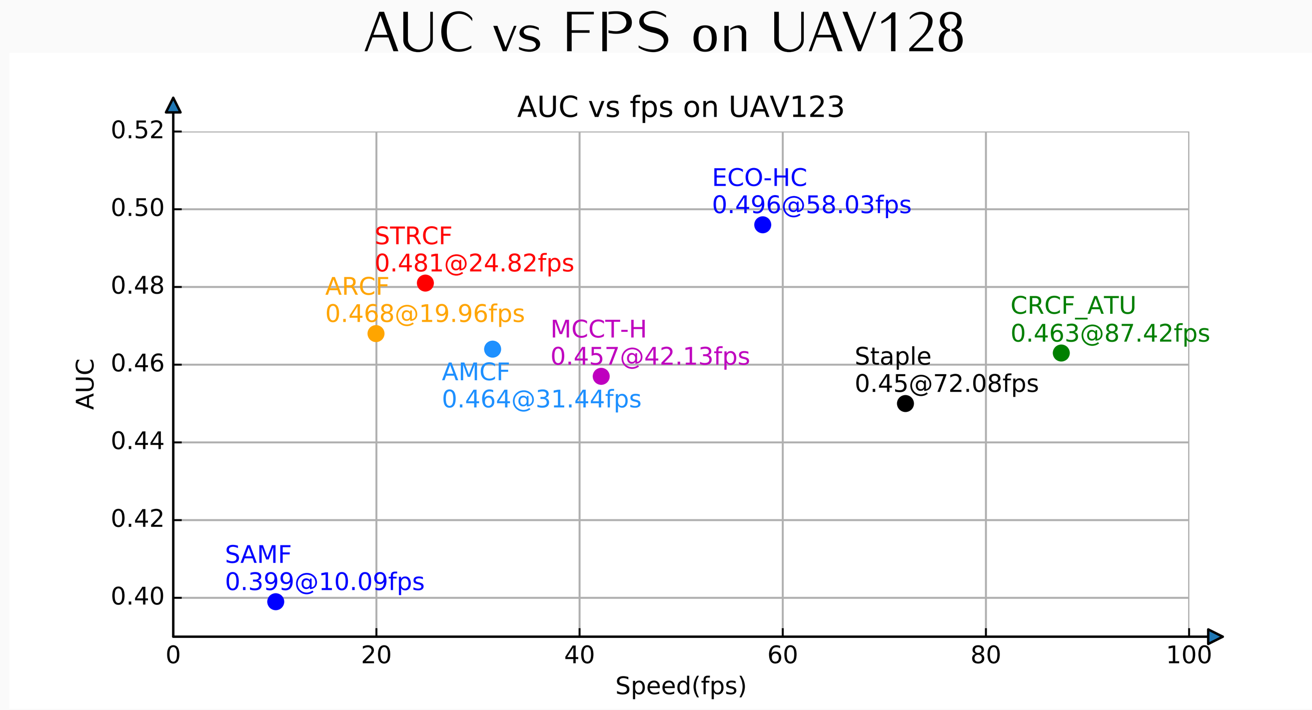
Temple Color 128

AUC vs FPS on Temple Color 128

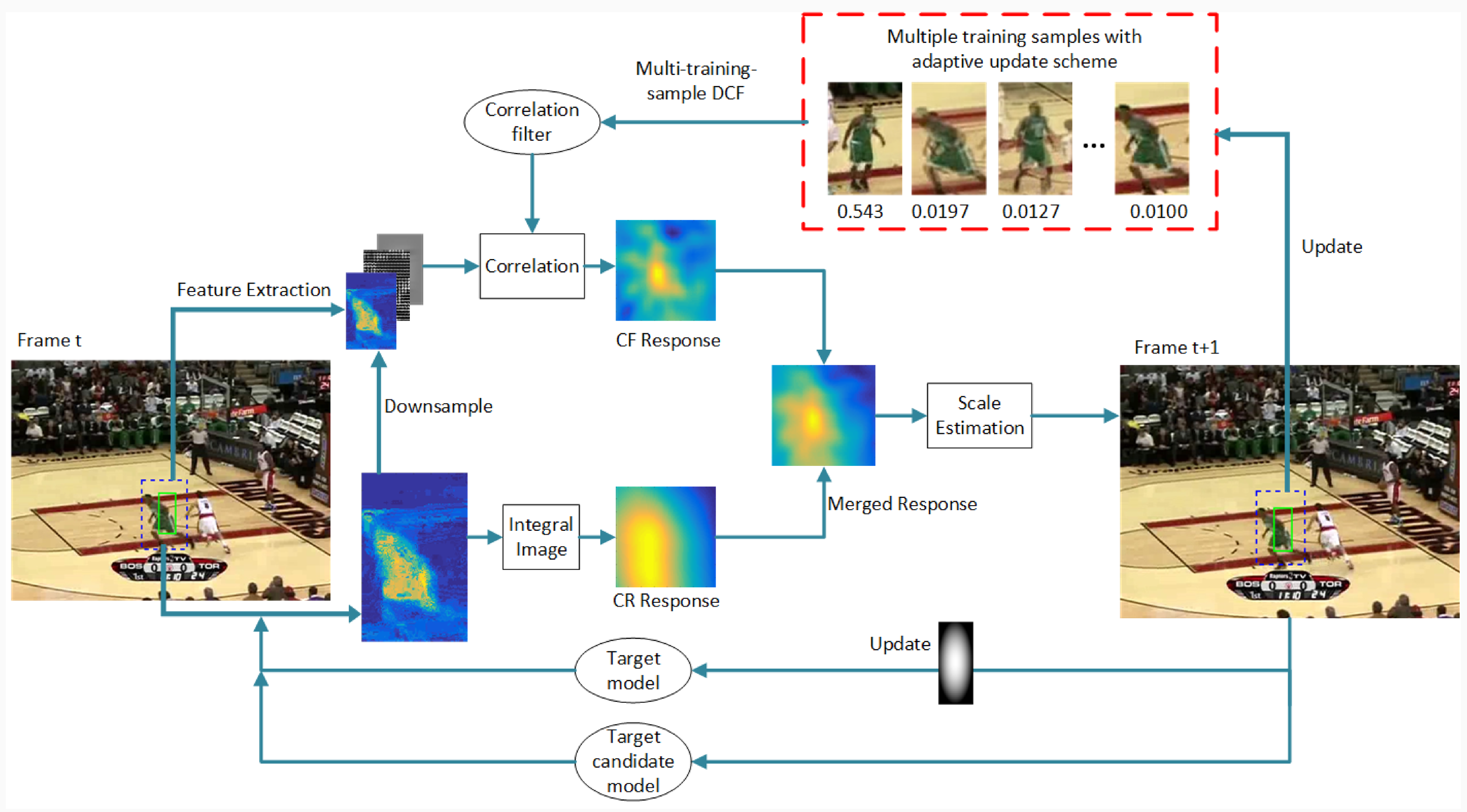


UAV123

AUC vs FPS on UAV128



Overall Sketch



Conclusion In this paper, we propose an efficient training sample update scheme and adaptively maintain a training set using difference hashing algorithm to train a multi-training-sample DCF. Experimental results on three benchmarks show that our tracker can achieve a close performance to state-of-the-art trackers with relatively light computation and high speed. The balance between performance and efficiency enables our tracker to be practical in computation restricted applications.