Efficient correlation filter tracking with adaptive training sample update scheme

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Introduction

- Visual object tracking is a basic research topic in the field of computer vision with widespread applications.

- In many applications such as UAV tracking and edge computing, the visual tracking module is required to run in high speed with restricted computing power.

- Recently, discriminative correlation filters (DCF) have attracted extensive attention for their outstanding performance and high efficiency in the field of visual tracking.

- Conventional DCF trackers suffer from boundary effects, restricting discriminative power and search region of the tracker.

- Spatially regularized DCF trackers without closed-form solution solve the filter in an iterative manner with high computational complexity and low speed.

- Simple moving average update scheme of usually leads to model drift and tracking failure under occlusion and large appearance variation.
Based on our previous CRCF tracker, we focus on the update scheme and propose CRCF_ATU with adaptive training sample update scheme.

Contributions:
1) Efficient CRCF_ATU tracker with outstanding performance suitable for real-time applications.
2) Adaptively update training set and measure sample distance with difference hashing algorithm.
3) Extend conventional DCF to multi-training-sample formulation with better generalization ability
Related Works

- Correlation filter based trackers
  - MOSSE
  - KCF
  - SRDCF, BACF, CSRDCF
  - deep features

- Model Update Scheme
  - Moving average on numerator and denominator
  - High confidence update strategy
  - C-COT: large training set
  - SRDCFdecon: Jointly learn sample weights
  - ECO: generative sample space model
  - STRCF: temporal regularization
Multi-training-sample DCF

We incorporate multiple training samples into traditional DCF formulation to minimize the following objective function

\[
E(h) = \sum_{k=1}^{N} \alpha_k \left\| \sum_{d=1}^{D} h_d^* x_{kd} - y \right\|^2 + \lambda \|h\|^2
\]

This minimizer has a closed-form solution in Fourier domain as

\[
\hat{h}_d = \frac{\sum_{k=1}^{N} \alpha_k \hat{x}_{kd}^* \odot \hat{y}}{\sum_{k=1}^{N} \sum_{d=1}^{D} \hat{x}_{kd}^* \odot \hat{x}_{kd} + \lambda}
\]
Adaptive training sample update scheme

We employ generative Gaussian model to maintain a training set of size N. In each frame, a new sample is updated to the training set according to distance between samples. To accelerate distance measurement, we adopt difference hashing algorithm (DHA). Each training sample is resized to 8x9 as \( \mathbf{B} \subseteq \mathbb{R}^{8 \times 9} \) to compute hashing matrix \( \mathbf{H} \subseteq \mathbb{R}^{8 \times 8} \) as

\[
h_{i,j} = \begin{cases} 
1, & \text{if } b_{i,j} > b_{i,j+1} \\
0, & \text{otherwise}
\end{cases}
\]

Sample distance are measured with hamming distance between their corresponding hashing matrices.

\[
d_{lc} = \sum_{i=1}^{8} \sum_{j=1}^{8} (h_{i,j}^c \oplus h_{i,j}^l)
\]

We find \( \tau(R) = \max(R) \cdot \text{APCE}(R) \) better reflect response reliability. Tracking result is considered to be unreliable 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.

\[
\frac{\tau(R_{CF})}{\bar{\tau}(R_{CF})} < T_{CF}, \quad \frac{\tau(R_{CR})}{\bar{\tau}(R_{CR})} < T_{CR}, \quad \frac{\tau(R)}{\bar{\tau}(R)} < T_R
\]
Experimental results

We conduct extensive experiments on **OTB2015**, **Temple-Color 128** and **UAV123** and plot the tracker performance (P20 and AUC) versus speed (FPS) and trackers on the top right corner exhibits better balance between performance and efficiency.

![AUC vs fps on OTB-2015](image_url)
Experimental results

AUC vs fps on Temple Color 128

- STRCF: 0.548@23.93fps
- MCCT-H: 0.552@54.41fps
- ECO-HC: 0.551@58.0fps
- CRCF_ATU: 0.54@100.22fps
- SRDCF: 0.485@10.12fps
- SAMF: 0.463@25.31fps
- Staple: 0.497@93.03fps
- DSST: 0.38@77.8fps
Experimental results

AUC vs fps on UAV123

- STRCF: 0.481@24.82fps
- ARCF: 0.468@19.96fps
- ECO-HC: 0.496@58.03fps
- MCCT-H: 0.457@42.13fps
- AMCF: 0.464@31.44fps
- CRCF_ATU: 0.463@87.42fps
- Staple: 0.45@72.08fps

SAMF: 0.399@10.09fps
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.
Thanks

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