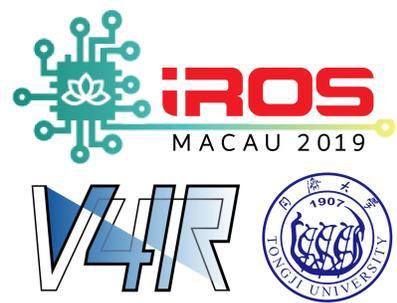


Sample Purification-Aware Correlation Filters for UAV Tracking with Cooperative Deep Features



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Introduction

Challenges & Motivations

- ▶ The representations of a single feature restrict the discriminant power of the correlation filter.
- **Cooperating deep features with different encoding ability**
- ▶ UAV tracking scenarios exist many challenging issues, e.g., viewpoint variations, the object/camera fast motion, occlusion, and background clutters, resulting in the corrupted training samples and suboptimal encoding ability of the appearance model.
- **Sample purification to construct the training set with high confidence**

Contribution 1: Cooperative features

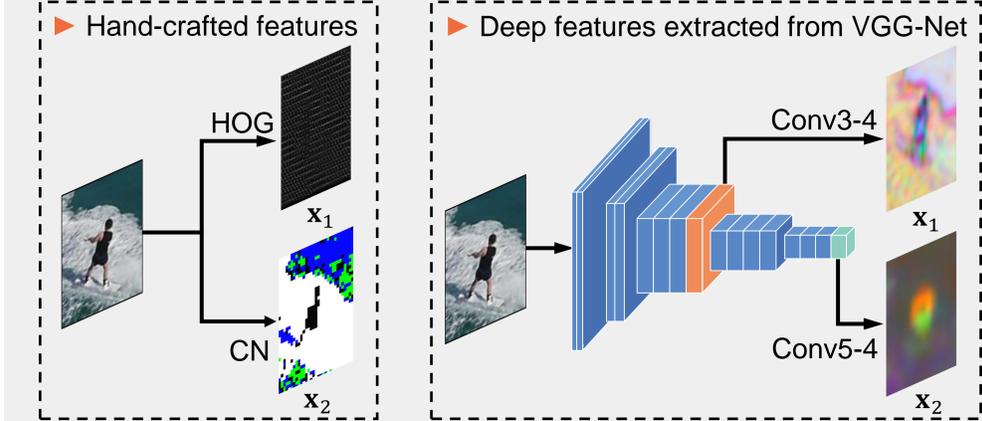
Objective

Learn multiple kernelized correlation filters for N different features

Loss function

$$\hat{\mathcal{L}}(\mathbf{w}_n^*) = \sum_{n=1}^N \left(\|\hat{C}_n(\mathbf{x}_n, \mathbf{x}_n) - \hat{y}_n\|_2^2 + \lambda_n \hat{\mathbf{k}}^{\mathbf{x}_n \mathbf{x}_n} \|\hat{\mathbf{w}}_n^*\|_2^2 \right) + \gamma \sum_{i,j=1}^N \|\hat{C}_i(\mathbf{x}_i, \mathbf{x}_i) - \hat{C}_j(\mathbf{x}_j, \mathbf{x}_j)\|_2^2$$

Optional features combination



Contribution 2: Sample purification

Objective

Integrate the sample weights $\{\alpha_n\}$ and temporal weights $\{t\}$ into the cooperative kernelized correlation filters

Loss function

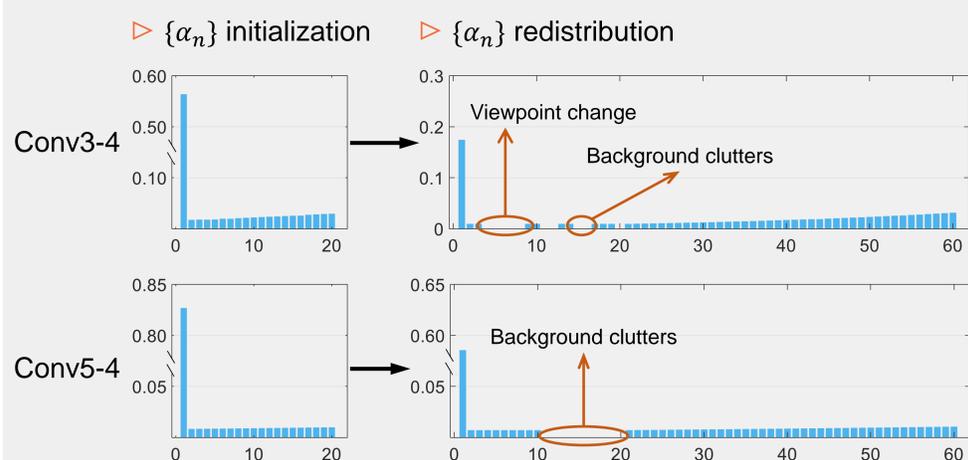
$$\hat{J}(\alpha_n^s, \mathbf{w}_n^*) = \sum_{n=1}^N \sum_{s=1}^S \alpha_n^s \left(\lambda_n \hat{\mathbf{k}}^{\mathbf{x}_n^s \mathbf{x}_n^s} \|\hat{\mathbf{w}}_n^*\|_2^2 + \|\hat{C}_n^s(\mathbf{x}_n^s, \mathbf{x}_n^s) - \hat{y}_n\|_2^2 \right) + \gamma \sum_{i,j=1}^N \sum_{s=1}^S \|\hat{C}_i^s(\mathbf{x}_i^s, \mathbf{x}_i^s) - \hat{C}_j^s(\mathbf{x}_j^s, \mathbf{x}_j^s)\|_2^2 + \sum_{n=1}^N \left(\mu_n \sum_{s=1}^S \frac{(\alpha_n^s)^2}{t^s} \right)$$

Remark

- ▶ The function is constituted by both \mathbf{w}_n^* and the sample weights $\{\alpha_n\}$.
- ▶ S is the number of samples in the training-set. s_0 is the most recent samples.
- ▶ $a = (S - s_0 + \frac{(1-q)^{-s_0-1}}{q})^{-1}$ is determined by the condition $\sum_s t^s = 1$. Each t^s is calculated as:

$$t^s = \begin{cases} a, & s = 1, \dots, S - s_0 \\ a(1-q)^{S-s_0-s}, & s = S - s_0 + 1, \dots, S \end{cases}$$

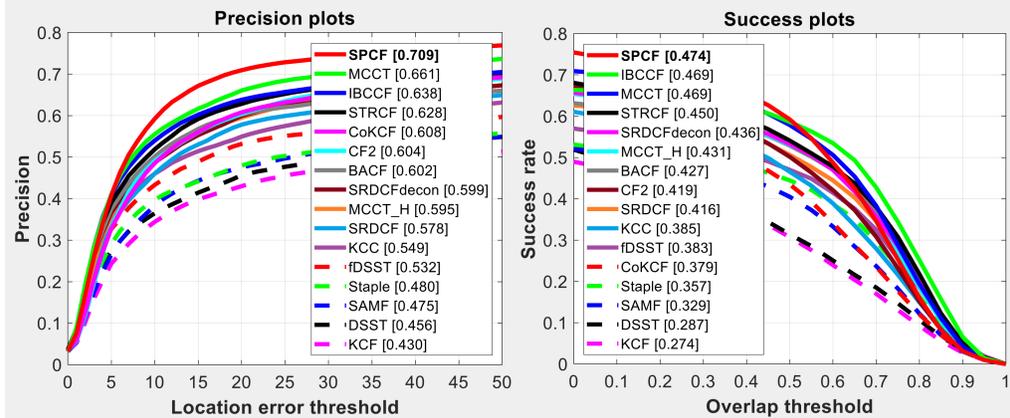
- ▶ Samples weights can update adaptively.



Experiments

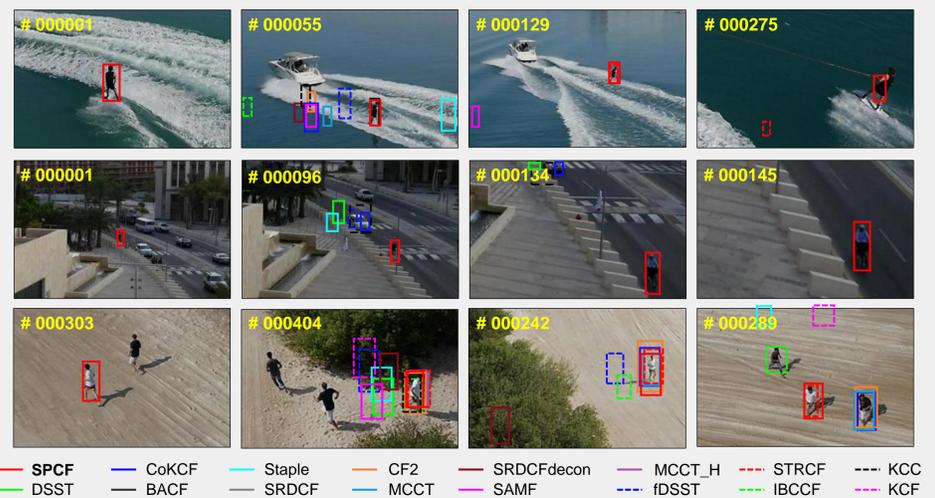
The UAV123 benchmark protocol [1] is used. Experimental results demonstrate that **SPCF** outperforms favorably against other 15 state-of-the-art trackers.

Overall performance



Examples of the UAV tracking results

The first, second, and third columns show the tracking results on the image sequences from *wakeboard3_1*, *bike3*, and *group2_2*.



Attribute-based performance

Attributes	Precision (CLE = 20 pixels)		Success (AUC score)	
	Best of others	SPCF	Best of others	SPCF
Camera motion	0.635	0.708	0.464	0.480
Fast motion	0.470	0.552	0.309	0.318
Partial occlusion	0.591	0.628	0.392	0.399
Viewpoint change	0.583	0.662	0.419	0.439
Aspect ratio change	0.573	0.644	0.387	0.401

Conclusion

- ▶ A new integrated learning method for multiple features is devised.
- ▶ A novel developed joint training framework is proposed to learn both sample weights and filters (**SPCF**).
- ▶ Extensive experiments on challenging UAV image sequences demonstrate that **SPCF** performs favorably against other 15 state-of-the-art trackers in accuracy and robustness.

Application

The SPCF tracker is also applied for various challenging tasks currently.



Reference

[1] M. Mueller, N. Smith, and B. Ghanem, "A benchmark and simulator for uav tracking," in Proceedings of the European Conference on Computer Vision (ECCV), 2016, pp. 445–461.

Source code

