Learning Residue-Aware Correlation Filters and Refining Scale Estimates with the GrabCut for Real-Time UAV Tracking

Shuiwang Li  Yuting Liu  Qijun Zhao  Ziliang Feng
College of Computer Science, Sichuan University
lishuiwang0721@163.com, yuting.liu@stu.scu.edu.cn, \{qjzhao, fengziliang\}@scu.edu.cn

Abstract

Unmanned aerial vehicle (UAV)-based tracking is attracting increasing attention and developing rapidly in applications such as agriculture, aviation, navigation, transportation and public security. Recently, discriminative correlation filters (DCF)-based trackers have stood out in UAV tracking community for their high efficiency and appealing robustness on a single CPU. However, due to limited onboard computation resources and other challenges the efficiency and accuracy of existing DCF-based approaches is still not satisfying. In this paper, we explore using segmentation by the GrabCut to improve the wildly adopted discriminative scale estimation in DCF-based trackers, which, as a matter of fact, greatly impacts the precision and accuracy of the trackers since accumulated scale error degrades the appearance model as online updating goes on. Meanwhile, inspired by residue representation, we exploit the residue nature inherent to videos and propose residue-aware correlation filters that show better convergence properties in filter learning. Extensive experiments are conducted on four UAV benchmarks, namely, UAV123@10fps, DTB70, UAVDT and Vistrone2018 (VisDrone2018-test-dev). The results show that our method achieves state-of-the-art performance.

1. Introduction

Unmanned aerial vehicle (UAV)-based tracking is an emerging task and has attracted increasing attention in recent years. It has various applications, e.g., aerial patrolling [30], disaster response [74], autonomously landing [43], wildlife protection [54]. Compared with general tracking scenes, UAV tracking faces more onerous challenges, e.g., motion blur, severe occlusion, extreme visual angle and scale change, and scarce computation resources [22]. Despite deep learning-based approaches have achieved great success and are promising in dealing with these challenges [14] [44] [65] [4] [34] [70], its efficiency is unsatisfactory in the limitation of power capacity and computational resources onboard UAVs. In contrast, discriminative correlation filters (DCF)-based methods are more favorable in efficiency for UAV tracking thanks to the fast Fourier transform (FFT) [29] [38] [23] [40] [32] [42] [39] [27] but they are not comparable with deep learning-based method in terms of precision and accuracy. One important reason is the failing to recognize the problems with the discriminative scale estimation [41] [18] used in DCF-based trackers. First, applying the filter at limited predefined multiple resolutions is inaccurate in estimating continuous changes of scale. Second, a fixed aspect ratio of target size is usually adopted to balance accuracy and speed in scale estimation, which is very rough and degrades the tracking greatly in situations where targets undergo extreme visual angle and appearance variations. See Fig. 1 for examples. As can be seen, the RACF tracker using the existing discriminative scale estimation performs badly when the two target cars undergo big visual angle changes. Therefore, the existing discriminative scale estimation is inaccurate, which in fact greatly impacts the precision and accuracy of the trackers, since accumulated scale error degrades the appearance model as online updating goes on. In this paper, we study using the segmentation algorithm GrabCut [57] to improve scale estimation of DCF-based trackers. The method is demonstrated by the tracker RACF shown in Fig. 1.
On the other hand, most DCF-based methods improve precision and accuracy at the cost of efficiency. For instance, the aberrance repressed correlation filters (ARCF) \[29\] has achieved state-of-the-art performance in UAV tracking by repressing aberrances happening during the tracking process, but it takes five iterations of ADMM (Alternating Direction Method of Multipliers) at each frame for model update, which is time-consuming compared with two iterations in its baseline the background-aware correlation filters (BACF) \[24\]. Inspired by the fast and stable optimization of Residual Networks (ResNets) \[26\], we exploit the residue nature inherent to videos and propose residue-aware correlation filters (RACF) that show better convergence properties in filter learning, which, to the best of our knowledge, has not been studied in DCF-based trackers before. In addition, ARCF does not use spatial and temporal regularizations which have been proved effective for suppressing boundary effects and avoiding overfitting to inaccurate and noisy samples \[15, 33, 36, 38\]. In this paper, we succeed to add spatial and temporal regularizations to boot performance with little additional computational cost. The contributions of this paper are summarized as follows:

- We propose a novel scale estimation approach for DCF-based trackers by using the GrabCut \[57\] algorithm to refine the discriminative scale estimates, which can be incorporated easily into any tracking method with discriminative scale estimation to improve precision and accuracy.

- We propose a novel regularization to model the residue between two neighboring frames, resulting in what we call residue-aware correlation filters, which show better convergence properties in filter learning. Meanwhile, we add spatial and temporal regularizations to boot performance with little additional computational cost.

- We demonstrate the proposed methods on four UAV benchmarks, namely, UAV123@10fps \[50\], DTB70 \[45\], UAVDT \[20\] and Vistrone2018 (VisDrone2018-test-dev) \[72\]. Experimental results show that the proposed approaches achieves state-of-the-art performance.

2. Related Works

2.1. Discriminative correlation filters

Using DCF for visual tracking starts with the minimum output sum of squared error (MOSSE) filter \[6\]. Afterwards, kernel trick \[28\], discriminative scale estimation \[41, 18\], spatial and temporal regularizations \[15, 33\], deep features \[46, 17\], attention \[27\], context and background information \[51, 24\] and so on were introduced for improvement. Among these DCF-based trackers, we are interested in the background-aware correlation filters (BACF) \[24\]. For one thing, it expands search region with lower computational cost and also has some theoretical advantages as shown in \[36\], an equivalent approach but formulated and optimized differently. For another, BACF equipped with an aberrance regularization and an enhanced feature extractor, i.e., the aberrance repressed correlation filters (ARCF) \[29\], has achieved state-of-the-art performance in multiple benchmarks specified for UAV tracking. These two methods are in close connection with our work here.

2.2. Residual representations

In visual tracking, residual learning was applied to capture the difference between the base layer output and the ground truth to reduce model degradation during online update in \[59\]. Before that residual representations had found their usefulness in image retrieval, recognition and restoration \[26, 64, 10\], video compression \[62\] and equation solving \[53\]. It has been shown \[61, 9\] that the solvers aware of the residual nature of the solutions converge much faster than standard solvers \[61, 53, 26\]. To understand the optimization landscape of the well-known ResNets \[26\], it has been proved that residual networks eliminate singularities and reduce shattered gradient, leading to numerical stability and easier optimization \[55, 3, 31\]. In the literature, residuals can be the difference between the target and the model output, the difference between the input and the output, the difference between a sample and the sample mean. In this paper, a residue is formed by subtracting the feature of the current frame from that of the previous one and the residual representation of the current frame is the sum of the residue and the feature of the previous frame. Since, approximately, videos are temporally continuous, the residues are usually of small values and entropy, which can be used to speed up the learning of correlation filters.

2.3. Scale estimation

There are three typical discriminative scale estimation strategies in DCF-based visual tracking \[48, 71\]. i) Multi-resolution translation filter (MRTF) defines a scale pool and estimates target scale by applying the translation filter on images of different scales \[41, 5\]. ii) Joint scale-space filter (JSSF) jointly estimates the translation and scale of the target by simultaneously maximizing the scores of translation and scale filters with a three-dimensional Gaussian function as the desired response. iii) Separate scale filter (SSF) learns a separate 1-dimensional scale correlation filter for scale estimation independent of translation \[19, 18\]. The SSF strategy has been popular in DCF-based trackers for its effectiveness, efficiency, robustness and easy integration. Although there are some variants such as using subgrid interpolation for efficiency \[18\], combining a points tracker for abrupt scale changes \[1\], defining rotation-aware corre-
4. Proposed Approach

4.1. Residue-aware correlation filters

The proposed residue-aware correlation filter with spatial and temporal regularizations is as follows:

\[
E(f_k) = \frac{1}{2} \| y - \sum_{d=1}^{D} x_k^{d} \ast P f_k^{d} \|_2^2 + \frac{\lambda}{2} \sum_{d=1}^{D} \| f_k^{d} \|_2^2 + \frac{\theta}{2} \sum_{d=1}^{D} \| \psi_{p,q} \|_2 \sum_{d=1}^{D} \| f_k^{d} - f_{k-1}^{d} \|_2^2 \]

where \( f_k^{d} = x_k^{d} - x_{k-1}^{d} \) denotes sample residue at the \( k \)th frame, \( w \) is a vectorized spatial regularization weight of bowl shape and \( \Delta_k \) denotes the Hadamard product. Parameters \( \eta, \theta, \tau \) are predefined penalty coefficients for residue-aware, spatial and temporal regularizations respectively. Eq. (3) will be transformed into the frequency domain and optimized with ADMM. Notice that the aberrance term of ARCF, i.e., \( \| M_{k-1}[\psi_{p,q}] - M_k \|_2^2 \) in Eq. (2), reduces to the proposed residue one, i.e., \( \| \Delta_k \ast P f_k^d \|_2^2 \) in Eq. (3), when \( \psi_{p,q} \equiv \psi_{0,0} = 0 \). As a reward of our formulation, the residue nature manifests itself and it takes only two iterations of ADMM at each frame in our algorithm, a considerable computational saving compared with five in ARCF.

4.1.1. Transformation into frequency domain

For efficiency, correlation filters are typically solved in the frequency domain. Let \( F \) denote the Fourier transform such that \( F^{-1} = F^H \), where the operator \( ^H \) computes the conjugate transpose on a complex vector or matrix, and \( \hat{z} = Fz \) be the Fourier transform of \( z \). Equipped with an auxiliary variable \( \hat{g}_k \), Eq. (3) can be expressed in the frequency domain as:

\[
E(f_k, \hat{g}_k) = \frac{1}{2} \| \hat{y} - X_k \hat{g}_k \|_2^2 + \frac{\theta}{2} \| \Delta_k \ast \hat{g}_k \|_2^2 + \frac{\tau}{2} \| f_k - f_{k-1} \|_2^2 + \frac{\lambda}{2} \| \hat{g}_k \|_2^2
\]

s.t. \( \hat{g}_k = (I_D \otimes F) f_k \)

where \( X_k = [\text{diag}(\hat{x}_k^1)^H, \ldots, \text{diag}(\hat{x}_k^D)^H] \), \( \Delta_k = [\text{diag}(\hat{\delta}_k^1)^H, \ldots, \text{diag}(\hat{\delta}_k^D)^H] \) and \( W = I_D \otimes \text{diag}(w) \). \( \text{diag}(w) \) denotes the diagonal matrix created by the vector \( w \) and \( \otimes \) indicates the Kronecker product. \( f_k = [(f_k^1)^H, \ldots, (f_k^D)^H]^H \) and \( \hat{g}_k = [(\hat{g}_k^1)^H, \ldots, (\hat{g}_k^D)^H]^H \) are vectors concatenating the corresponding \( D \) vectorized channels.
4.1.2 Optimization with ADMM

The augmented Lagrangian of Eq. (4) is as follows,

\[ L(f_k, g_k, \hat{\zeta}) = \frac{1}{2} ||\hat{y} - X_k g_k||^2 + \frac{\eta}{2} ||\Delta_k g_k||^2 + \frac{\theta}{2} ||Wf_k||^2 + \frac{\tau}{2} ||f_k - f_{k-1}||^2 + \frac{\lambda}{2} ||f_k||^2 + \hat{\zeta}^H (g_k - (I_D \otimes FP)f_k) + \frac{\mu}{2} ||g_k - (I_D \otimes FP)f_k||^2, \]

(5)

where \( \mu \) is the penalty coefficient and \( \hat{\zeta} = [\hat{\zeta}_1, ..., \hat{\zeta}_D]^T \) is the Lagrangian vector of size \( DN \times 1 \) in the frequency domain. Eq. (5) is solved iteratively using the ADMM at the \( k \)th frame. Fortunately, closed form solutions can be found for each of the following subproblems.

**Subproblem \( f_k^* \)**

\[ f_k^* = \arg \min_{f_k} \left\{ \frac{\theta}{2} ||Wf_k||^2 + \frac{\tau}{2} ||f_k - f_{k-1}||^2 + \frac{\lambda}{2} ||f_k||^2 + \hat{\zeta}^H (g_k - (I_D \otimes FP)f_k) + \frac{\mu}{2} ||g_k - (I_D \otimes FP)f_k||^2 \right\}, \]

(6)

where \( g_k = (I_D \otimes P^T P^H) g_k \) and \( \zeta = (I_D \otimes P^T P^H) \hat{\zeta} \), which can be broken into \( D \) independent \( P^T P^H \) transforms in realization. Since \( A = (\mu + \lambda + \tau)I + \theta W^H W \) is a diagonal matrix, its inverse (if it exists) can be computed immediately. In fact, \( A^{-1} \) multiplying by \( (\mu g_k + \zeta + \tau f_{k-1}) \) can be conducted simply by dot division.

**Subproblem \( g_k^* \)**

\[ g_k^* = \arg \min_{g_k} \left\{ \frac{1}{2} ||\hat{y} - X_k g_k||^2 + \frac{\eta}{2} ||\Delta_k g_k||^2 + \hat{\zeta}^H (g_k - (I_D \otimes FP)f_k) + \frac{\mu}{2} ||g_k - (I_D \otimes FP)f_k||^2 \right\}. \]

(7)

It is burden to directly solve Eq. (7). Fortunately, each entry of \( \hat{y} \), i.e., \( \hat{y}(n) \), depends only on \( \hat{x}_k(n) = [\hat{x}_k^1(n), ..., \hat{x}_k^D(n)]^T \), \( \delta_k(n) = [\delta_k^1(n), ..., \delta_k^D(n)]^T \) and \( \tilde{g}_k(n) = [\tilde{g}_k^1(n), ..., \tilde{g}_k^D(n)]^T \), \( n = 1, 2, ..., N \). Therefore, the subproblem \( g_k^* \) can be divided into \( N \) smaller problems as follows:

\[ g_k^* (n) = \arg \min_{g_k(n)} \left\{ \frac{1}{2} ||\hat{y}(n) - \hat{x}_k(n)||^2 + \frac{\eta}{2} ||\Delta_k(n) g_k(n)||^2 + \hat{\zeta}^H (\tilde{g}_k(n) - \hat{f}_k(n)) + \frac{\mu}{2} ||g_k(n) - \hat{f}_k(n)||^2 \right\}, \]

(8)

where \( \hat{f}_k(n) = [\hat{f}_k^1(n), ..., \hat{f}_k^D(n)]^T \) and \( \hat{f}_k^d \) is the Fourier transform of padded \( f_k^d \), i.e., \( f_k^d \) is the Fourier transform of \( f_k \). The solution for \( \hat{g}_k^*(n) \) is as follows,

\[ \hat{g}_k^*(n) = \left( \mu I_D + \eta \delta_k(n) \delta_k^H(n) + \hat{x}_k(n) \tilde{g}_k^H(n) \right)^{-1} \left( \hat{y}(n) \tilde{g}_k(n) + \mu \hat{f}_k(n) - \hat{\zeta}(n) \right). \]

(9)

The matrix inversion in Eq. (9) can be got rid of by applying twice the Sherman-Morrison formula \[ \frac{1}{I + uv^H} = I - \frac{uv^H}{1 + v^H u}, \] i.e., \( A = I + \eta \delta_k(n) \delta_k^H(n) + \hat{x}_k(n) \tilde{g}_k^H(n) \) is then used to solve \( \hat{g}_k^*(n) \) first and then \( A^{-1} = \mu I_D + \eta \delta_k(n) \delta_k^H(n) + \hat{x}_k(n) \tilde{g}_k^H(n) \). After further simplification, we have

\[ \hat{g}_k^*(n) = A^{-1} \omega \hat{x}_k(n) + \mu \hat{f}_k(n) - \hat{\zeta}(n), \]

(10)

where \( \omega \) is defined by

\[ \omega = \frac{\hat{y}(n) \tilde{g}_k(n) + \mu \hat{x}_k(n) A^{-1} \tilde{g}_k(n) - \hat{x}_k(n) \tilde{g}_k^H(n) \hat{f}_k(n)}{(1 + \hat{x}_k(n) A^{-1} \tilde{g}_k(n))}, \]

(11)

in which \( A^{-1} = \frac{1}{\mu} (I_D - \frac{\eta \delta_k(n) \delta_k^H(n)}{\mu + \eta \delta_k(n) \delta_k^H(n)}) \). The terms of forms \( A^{-1} \) and \( \mu A^{-1} \) in Eq. (10) and Eq. (11), respectively, can be computed effectively by inner product of vectors.

**Update of the Lagrangian \( \hat{\zeta} \)**

The Lagrangian is updated according to:

\[ \hat{\zeta}^{(i+1)} = \hat{\zeta}^{(i)} + \mu (\hat{g}_k^{(i+1)} - \hat{f}_k^{(i+1)}) \]

(12)

where \( \hat{f}_k^{(i+1)} = (I_D \otimes FP)f_k^{(i+1)} \) and \( \hat{g}_k^{(i+1)} \) are the current solutions to the two subproblems at iteration \( (i + 1) \) within ADMM and \( \mu \) is set with the scheme \( \mu^{i+1} = \min(\mu_{max}, \beta \mu^{i}) \).

4.1.3 Update of appearance model

To improve robustness, the appearance model is adopted online \[ \hat{x}_k^{model} = (1 - \alpha) \hat{x}_{k-1}^{model} + \alpha \hat{x}_{k-1} \]

(13)

where \( \alpha \) is the adaptation rate of the appearance model. \( \hat{x}_k^{model} \) instead of \( \hat{x}_k \) is then used to solve \( \hat{g}_k^* \).

4.1.4 Target localization

Spatial location of the target in the \((k + 1)\)th frame is localized by searching for the maximum value of response map \( R_{k+1} \) which is calculated by:

\[ R_{k+1} = F^{-1} \left( \sum_{d=1}^{D} (\text{conj}(\hat{z}_{k+1}^d) \odot \hat{g}_k^d) \right) \]

(14)
where $\hat{z}_{k+1, \ldots}^d$ denotes the Fourier transform of extracted feature in the $(k+1)$th frame. Operator $\text{conj}(.)$ denotes the complex conjugate operation.

### 4.2. Refine scale estimates with the GrabCut

As a graph cut \cite{8} based method, GrabCut is not only promising to specific images with known information but also effective to the natural images without any prior knowledge. It uses a Gaussian mixture model \cite{49} to estimate the pixel color distribution of the object and background from a user specified bounding box around the segmented object, which is then used to construct a Markov random field \cite{8} over the pixel labels with an energy function that prefers connected regions having the same label.

One disadvantage of it is the need for initial user interaction to initialize the segmentation process with a bounding box. Fortunately, in our scenario, we can adapt, by appropriately enlarging, the estimate of SSF to provide such an initial bounding box, which, hopefully, contains background as little as possible with the whole target being inside. Another disadvantage is, GrabCut may produce unacceptable results in the cases of low color contrast between the foreground and the background or high contrast among the foreground itself. Since we intend to exploit the accuracy of the GrabCut for refining, it is very important to refine the scale estimate of SSF only with acceptable segmentation by the GrabCut. Since for an effective SSF-based tracker the IoU (intersection over union) of the scale estimated by SSF with ground truth is supposed to be above a certain value in order to maintain the effectiveness of the appearance model, the IoU between the scale estimated by SSF and the GrabCut above a certain threshold is used as the condition in this paper for conducting scale refinement to alleviate accumulating scale errors. The last but not least, although the GrabCut can achieve globally optimal result in polynomial time \cite{57}, it is still slow for UAV tracking if the input to the GrabCut is large. Therefore the input to the GrabCut is resized to a fixed and relatively small size to balance effectiveness and efficiency.

### 4.3. Our tracking framework

Fig. 2 illustrates the overview of the proposed algorithm for visual tracking. The translation filter $f_k$, formulated in the section 4.1, adapts to appearance changes of the target and its surrounding context for estimating translation. The 1D scale filter $h_k$ predicts scale variation of the target is the same as in \cite{18, 24, 29}. The location of the target in the $(k+1)$th frame, denoted by $p^*_{k+1}$, is estimated by applying $f_k$ that has been updated in the $k$th frame to the detection sample extracted from the current frame at the last position $p^*_k$. Afterwards, $h_k$ is applied at multiple resolutions to estimate the scale of the target size, denoted by $s_1$. At last, the proposed scale refinement is carried out. Firstly, an extended example is extracted centered at $p^*_{k+1}$ with size of $\frac{s_1}{5}$, which is associated a smaller bounding box of size $s_1 + \Delta s, \Delta s < 0.5s_1$, centered also at $p^*_k$. The extended example and the bounding box will be scaled to fixed sizes $s_g$ and $\left[\frac{s_1}{3}(1+\frac{\Delta s}{s_1})s_g\right]$, respectively, to make the input image and the initial bounding box for the GrabCut. Then the GrabCut is run to get the binary mask representing the foreground, the minimum bounding box of which, after resized, consists of the estimated scale $s_2$ by the GrabCut. Finally, the refined scale is defined by

$$s^*_{k+1} = \begin{cases} s_1, & \text{if } \text{IoU}(s_1, s_2) > \sigma, \\ s_2, & \text{otherwise} \end{cases}$$

(15)
where \( \text{IoU}(s_1, s_2) \) computes the IoU between \( s_1 \) and \( s_2 \) and \( \sigma \) is a predefined threshold.

### 5. Experiments

In this section, the proposed trackers with different components, summarized in Table 1, are exhaustively evaluated on four challenging UAV benchmarks, namely, UAV123@10fps [50], DTB70 [35], UAVDT [20] and Vistrone2018 [72]. UAV123@10fps is designed to investigate the impact of camera capture speed on tracking performance and constructed by down sampling the UAV123 benchmark [50] to 10 FPS from 30FPS. DTB70 composed of 70 UAV sequences primarily addresses the problem of severe UAV motion, but includes as well various cluttered scenes and objects with different sizes. UAVDT is mainly for vehicle tracking with various weather conditions, flying altitudes and camera views. Vistrone2018 (VisDrone2018-test-dev) [22]. UAV123@10fps is designed to investigate the impact of camera capture speed on tracking performance and constructed by down sampling the UAV123 benchmark [50] to 10 FPS from 30FPS. DTB70 composed of 70 UAV sequences primarily addresses the problem of severe UAV motion, but includes as well various cluttered scenes and objects with different sizes. UAVDT is mainly for vehicle tracking with various weather conditions, flying altitudes and camera views. Vistrone2018 (VisDrone2018-test-dev) [22].

| Residue-aware regularization | RACF⊖⊖ | RACF⊖ | RACF |
|-----------------------------|--------|-------|------|
| ✓                           | ✓      | ✓     | ✓    |
| Spatial & temporal regularizations | ✓ | ✓ | ✓ |
| Scale refinement            | ✓      | ✓     | ✓    |

### 5.1. Comparison with hand-crafted based trackers

Thirteen state-of-the-art trackers based on hand-crafted features for comparison are: AutoTrack [38], ARCF-HC [29], STRCF [33], MCCT-H [69], KCC [66], ECO-HC [13], BACF [24], Staple-CA [52], CSRDCF [45], fDSST [16], KCF [28], DSST [19] and SAMF [41]. The precision and success plots on four benchmarks are shown in Fig. 3. Besides, the average performance in terms of frames per second (FPS) and precision is displayed in Table 2.

### Overall performance evaluation:

Fig. 3 shows the overall performance of RACF with the competing trackers on the four benchmarks. As can be seen, RACF outperforms all other trackers on all benchmarks. Specifically, on UAV123@10fps and DTB70, RACF outperforms the second tracker AutoTrack in (precision, AUC) with gains of (2.3%, 0.9%) and (0.9%, 2.7%) respectively. On UAVDT, RACF surpasses the second place, i.e, ARCF-HC, by a significant gain of (5.3%, 3.6%). RACF also achieved the best performance on Vistrone2018, followed by ECO-HC with a gap of (2.9%, 1.6%). In terms of speed, we evaluate the average FPS of RACF, RACF⊖ and RACF⊖⊖ with the competing trackers on the four benchmarks, the FPSs along with the average precisions are shown in Table 2. As can be seen, RACF⊖⊖ has already outperformed state-of-the-
Attribute-based evaluation: The proposed RACF outperforms other hand-crafted based trackers in most attributes defined respectively in the four benchmarks. Examples of success plots are shown in Fig. 4. In the situations of deformation, viewpoint change and scale variations, RACF demonstrates a significant improvement over other trackers because of the effectiveness of the proposed scale refinement in the corresponding benchmarks. All results are displayed in the supplementary materials.

Qualitative evaluation: Some qualitative tracking results of RACF and four top trackers are shown in Fig. 5. It can be seen that the scale estimates of RACF are more accurate in these examples with challenging viewpoint change, deformation and scale variations, justifying the effectiveness of the proposed method for refining scale estimates.

5.2. Comparison with deep-based trackers

The proposed RACF is also compared with fifteen state-of-the-art deep trackers, i.e., KYS [4], D3S [44], SiamR-CNN [65], PrDiMP18 [14], ASRCF [12], UDT+ [67], TADT [37], DeepSTRFC [33], MCCT [68], DSiam [24], ECO [13], ADNet [75], CFNet [63], MCPF [76] and CREST [59]. RACF achieves the second best precision and its CPU speed surpasses most GPU speeds on the UAVDT benchmark as shown in Table 3.

5.3. Ablation study

Residue-aware regularization: To see how the number of ADMM iterations impacts the success rate of BACF, ARCF-HC and RACF⊖⊖, respectively, we evaluate the three trackers on DTB70 with varied ADMM iterations. The variations of success rate with respect to the number of ADMM iterations are shown in Table 4. As can be seen, RACF⊖⊖ obtains the highest success rate at iteration 2,
Table 4. Illustration of how success rate on DTB70 varies with the number of ADMM iterations in RACF⊖⊖ and the two baselines, i.e., BACF [24] and ARCF-HC [29]. The best success rates and the ones corresponding to default parameter settings are shown in red and underline, respectively.

| Tracker     | Iter. | 1   | 2   | 3   | 4   | 5   | 6   | 7   | 8   | 9   | 10  | 15  | 20  | 25  |
|-------------|-------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| BACF [24]   |       | 23.113 | 40.201 | 41.016 | 40.864 | 40.695 | 40.866 | 40.845 | 40.577 | 40.72 | 40.773 | 40.433 | 40.615 |
| ARCF-HC [29] |       | 29.609 | 46.362 | 45.785 | 46.806 | **47.171** | 47.103 | 47.136 | 47.255 | 47.261 | 47.254 | **47.482** | 46.357 | 46.772 |
| RACF⊖⊖      |       | 27.550 | **48.246** | 48.184 | 47.893 | 47.939 | 47.929 | 47.951 | 47.989 | 47.989 | 47.993 | **47.903** | 47.972 | 47.871 |

Table 5. AUCs and precisions on the four benchmarks. PRC is short for precision, and SR represents the scale refinement component. Red, green and blue respectively mean the first, second and third place.

| Methods | UAV123@10fps | DTB70 | UAVDT | Vistrone2018 | Avg. |
|---------|--------------|-------|-------|--------------|------|
| ECO-HC w/wo SR | 46.247/47.17/46.046/46.3046 | 63.4/66.0/63.406/63.406 | 45.3/46.0/45.306/45.3/46.0 | 64.3/64.6/64.3/64.6 | 41.0/46.5/41.0/46.5 |
| ARCF-HC w/wo SR | 47.347/48.1/46.9/46.909 | 66.6/66.6/66.6 | 47.12/47.9/47.1/47.9 | 47.5/47.9/47.5/47.9 | 45.8/49.3/45.8/49.3 |
| AutoTrack w/wo SR | 47.748/47.3/47.1/47.1 | 67.1/67.1/67.1 | 47.28/47.1/47.2/47.1 | 47.6/47.1/47.6/47.1 | 45.0/48.2/45.0/48.2 |
| RACF⊖⊖ | 47.8/47.8/47.8 | 69.1/69.1/69.1 | 48.5/48.5/48.5 | 70.7/70.7/70.7 | 46.6/46.6/46.6 |
| RACF | 48.6/48.6/48.6 | 69.4/69.4/69.4 | 50.5/50.5/50.5 | 72.5/72.5/72.5 | 46.6/46.6/46.6 |

Table 6. Illustration of how success rate on DTB70 varies with η and the number of ADMM iterations in RACF⊖⊖. The best success rates are shown in red.

| Iter. | η | 0.2 | 0.4 | 0.6 | 0.8 | 1.0 | 1.2 | 1.4 | 1.6 |
|-------|---|-----|-----|-----|-----|-----|-----|-----|-----|
| 1     |   | 46.782 | 47.695 | 47.921 | 47.982 | 47.754 | 47.674 | 47.287 |
| 2     |   | 46.590 | 46.977 | 47.903 | 46.098 | 46.246 | 46.971 | 47.031 | 47.203 |
| 3     |   | 47.039 | 48.879 | 47.712 | 47.544 | 48.184 | 47.683 | 46.595 | 46.572 |
| 4     |   | 47.018 | 46.843 | 47.752 | 47.522 | 47.893 | 47.190 | 46.651 | 46.595 |
| 5     |   | 47.018 | 46.843 | 47.752 | 47.522 | 47.893 | 47.190 | 46.651 | 46.595 |
| 6     |   | 47.018 | 46.806 | 47.752 | 47.522 | 47.893 | 47.190 | 46.700 | 46.595 |
| 7     |   | 47.018 | 46.806 | 47.752 | 47.522 | 47.893 | 47.190 | 46.700 | 46.595 |
| 8     |   | 47.018 | 46.806 | 47.752 | 47.522 | 47.893 | 47.190 | 46.700 | 46.595 |
| 9     |   | 47.018 | 46.806 | 47.752 | 47.522 | 47.893 | 47.190 | 46.700 | 46.595 |
| 10    |   | 47.018 | 46.796 | 47.839 | 47.521 | 47.898 | 47.189 | 46.651 | 46.595 |
| 15    |   | 47.035 | 46.773 | 47.843 | 47.521 | 47.903 | 47.152 | 46.660 | 46.591 |
| 20    |   | 47.029 | 46.773 | 47.640 | 47.526 | 47.872 | 47.155 | 46.660 | 46.544 |
| 25    |   | 47.029 | 46.747 | 47.590 | 47.540 | 47.871 | 47.155 | 46.680 | 46.541 |

BACF at iteration 3 and ARCF-HC at iteration 15, justifying that RACF⊖⊖ converges faster in average. We can also see that the fluctuations after iteration 2 are basically smaller in RACF⊖⊖ than in the others. To study the impact of η, the penalty of residue-aware regularization, we show in Table 6 the success rates of RACF⊖⊖ on DTB70 with respect to both η and the number of ADMM iterations. As shown, RACF⊖⊖ achieves the highest success rate when η = 1.0 at iteration 2. Notice that for each value of η the highest success rate is obtained at iteration either 2 or 3, which conforms the fast convergence of the method.

Scale refinement, spatial and temporal regularizations: We incorporate the scale refinement (SR) component into three state-of-the-art trackers, i.e., ECO-HC, ARCF-HC and AutoTrack, to validate its effectiveness and generality. The AUC and PRC, short for precision, on the four benchmarks are shown in Table 5. Equipped with SR, ECO-HC, ARCF-HC and AutoTrack acquire in average, respectively, gains of (2.1%, 2.0%), (1.7%, 1.9%) and (1.7%, 1.6%) in (AUC, PRC). The most significant improvements, specifically (5.5%, 4.6%), (3.5%, 5.7%) and (3.2%, 3.4%), are observed on UAVDT, for whose foreground and background are basically cars and roads and the GrabCut works well in these cases. The AUC and PRC of the proposed trackers are also shown in Table 5 beneath the dash line. As can be seen, in average, the SR component makes a gain of (1.6%, 1.3%) in (AUC, PRC), while the spatial and temporal regularizations make a gain of (0.8%, 1.3%), justifying the effectiveness of both components.

6. Conclusion

In this work, we proposed and evaluated the residue-aware correlation filters and the method of refining scale estimates with the GrabCut. The proposed RACF surpasses all state-of-the-art hand-crafted based trackers in terms of precision and success rate in all the four UAV benchmarks and is comparable as well to many state-of-the-art deep-based trackers on UAVDT. The proposed scale refinement component can be easily incorporated into any tracking method with discriminative scale estimation to improve precision and accuracy.
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