DCF-ASN: Coarse-to-fine Real-time Visual Tracking via Discriminative Correlation Filter and Attentional Siamese Network

Abstract

Discriminative correlation filters (DCF) and siamese networks have achieved promising performance on visual tracking tasks thanks to their superior computational efficiency and reliable similarity metric learning, respectively. However, how to effectively take advantages of powerful deep networks, while maintaining the real-time response of DCF, remains a challenging problem. Embedding the cross-correlation operator as a separate layer into siamese networks is a popular choice to enhance the tracking accuracy. Being a key component of such a network, the correlation layer is updated online together with other parts of the network. Yet, when facing serious disturbance, fused trackers may still drift away from the target completely due to accumulated errors. To address these issues, we propose a coarse-to-fine tracking framework, which roughly infers the target state via an online-updating DCF module first and subsequently, finely locates the target through an offline-training asymmetric siamese network (ASN). Benefiting from the guidance of DCF and the learned channel weights obtained through exploiting the given ground-truth template, ASN refines feature representation and implements precise target localization. Systematic experiments on five popular tracking datasets demonstrate that the proposed DCF-ASN achieves the state-of-the-art performance while exhibiting good tracking efficiency.

Keywords: Visual tracking · correlation filter · attentional siamese network · coarse-to-fine strategy

1 Introduction

Visual tracking, which tracks an arbitrary temporally changing object based on the specified ground truth at the first frame, plays an active role in a wide range of applications, including robotics, surveillance, human–computer interaction and motion analysis. However, fast motion, partial or full occlusion, background clutter and many other factors in the image sequences make it a challenge to perform effective and efficient tracking. How to estimate the target state in complex scenarios with balanced accuracy and speed is the core problem of this task.

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DCF-ASN: Coarse-to-fine Real-time Visual Tracking

Figure 1: Illustration of "coarse-to-fine" strategy on sequences S1607 and Girl2 obtained from datasets UAVDT and OTB100. After DCF guided sampling, proposed DCF-ASN is able to relocate the target missed by the DCF.

Benefiting from cycle shift operation and fast Fourier transform (FFT), discriminative correlation filter (DCF) [Huang et al. 2020] based trackers are popular for their efficiencies among the existing tracking algorithms. They learn to discriminate an image patch from the surrounding patches by solving a ridge regression problem and calculating the correlation response in the frequency domain. More recently, research on visual tracking has focused on deep learning based methods [Li et al. 2018a, Chen et al. 2020, Danelljan et al. 2020]. Much attention has been paid into siamese networks [Xiao et al. 2020], which always extract deep features and then locate the target by measuring the similarity of extracted features. Although trained through the large scale datasets, the early siamese trackers have not been able to achieve state-of-the-art (SOTA) performance. The follow-on methods as reported in Valmadre et al. [2017], Danelljan et al. [2019], Bhat et al. [2019] obtain certain improvements by employing online-updating rules and embedding a cross-correlation layer into siamese structure. However, such an online-updating tracker based on end-to-end siamese network may drift away if inevitable tracking errors become serious. Recent work as per siamese-RPN [Li et al. 2018b] found that an offline trained deep tracker could also achieve competitive results without online adaptation. Inspired by these observations, an efficient coarse-to-fine tracking framework is proposed in this paper, where the online updating DCF module first predicts target position coarsely and the offline trained siamese network performs fine target localization. The contribution of this work is three-fold:

1. We present a coarse-to-fine visual tracking framework via an online updating DCF and an offline learned siamese network, in which two modules correct and promote each other (See Figure 1).
2. We propose a novel attentional siamese network (ASN) to learn the appropriate channel weights from a given template through off-line training, offering more powerful and robust weighted feature maps for accurate bounding box regression.
3. The proposed tracking framework achieves competitive performance on 7 popular benchmarks of OTB100, VOT2018, LaSOT, GOT10K, TrackingNet, UAV123 and UAVDT, while performing at real-time speed. Both qualitative and quantitative analyses demonstrate of robustness of the proposed tracker.

2 Related Work

**Discriminative correlation filter based tracking:** DCF trackers perform fast tracking through circular convolution, which can be implemented efficiently through transformation to the frequency domain. The first application of correlation filters for tracking was presented in Bolme et al. [2010], which worked by manipulating the maximum cross-correlation response between the target and the candidate patches. Following this initial approach, a number of improvements over the DCF trackers have been introduced, including those based on: kernel space [Henriques et al. 2014], multi-scale filters [Danelljan et al. 2014], traditional fused features [Bertinetto et al. 2016a], spatial-regularization operates [Li et al. 2018c], and factorized convolution [Danelljan et al. 2017]. In light of the effectiveness of deep convolutional neural networks (CNNs), other algorithms [Danelljan et al. 2017, Wang et al. 2018a] have been developed that experience an increase on tracking accuracy when employing a pretrained deep network to produce features [He et al. 2016]. However, the full potential of deep CNNs in performing tracking tasks has not been exploited by the offline trained feature extractor.
Siamese network based tracking: Siamese trackers each consist of two branches, which encode different patches into feature maps and compare their similarities in the implicitly embedded space. Inspired by correlation based methods, the pioneering work SiamFC [Bertinetto et al., 2016b] introduces a cross-correlation layer, thereby achieving beyond real-time speed. However, there remains a significant gap between SiamFC and the SOTA techniques in terms of online adaptability. As a follow-up work, CFNet [Valmadre et al., 2017] breaks through this bottleneck by constructing an end-to-end online updating siamese network. Aiming to be adaptable to the appearance variation of the target, DSiam [Guo et al., 2017] employs fast transformation learning and multi-layer fusion, which supports adaptively integrating the network outputs. Apart from these approaches, other popular optimization methods include those that exploit triplet loss [Dong and Shen, 2018], introduce residual attention learning [Wang et al., 2018b] and anchor-free mechanism [Chen et al., 2020], and impose the width and depth of a network [Zhang and Peng, 2019] or semantic mask branch [Wang et al., 2019]. Additionally, learning from object detection methods, there exist further approaches [Danelljan et al., 2020, 2019, Li et al., 2018b] that consider the tracking task as a one-shot detection problem, which perform well with the assistance of large-scale training image pairs.

3 Coarse-to-fine Tracking Framework

In order to fully adapt to the change of target appearance while suppressing potential model drift caused by online updating, we propose a novel coarse-to-fine tracking framework. As displayed in Figure 2, it consists of two components: a discriminative correlation filter for coarse target prediction and a class-agnostic attentional siamese network (ASN) for precise localization. The target estimation network in ATOM [Danelljan et al., 2019] is adopted as the baseline to design the proposed ASN. The complete procedure of DCF-ASN is shown in Algorithm 1.

3.1 DCF based coarse target prediction

The DCF module is utilized to roughly estimate the target state in the proposed framework, and the structure of the filter itself is very simple in an effort to reduce the additional computation. Sharing the same feature extractor with ASN, the DCF module represents the $i$-th $(i \in [1, D])$ layer feature of sample $j$ – $th (j \in [1, N])$ as $x_{ji}$, and the online
By applying FFT to convert the learned filter from the temporal to the frequency domain, we can rewrite (1) as:

$$L(\omega; x) = \sum_{j=1}^{N} \sum_{i=1}^{D} \mu_{ji} \left\| F(W, X_{ji}) - Y_{ji}\right\|^2 + \sum_{i=1}^{D} \left\| \lambda * F^i \right\|^2$$ (2)

where each capital letter stands for the corresponding form of the original temporal variable.

Making full use of the sparsity structure of this problem as (2), the DCF module proposed herein utilizes the Conjugate Gradient method (CG) [Danelljan et al. 2017] to resolve it efficiently, computing the target state in the frequency domain. After transforming the optimal result back to the time domain by inverse FFT, the resulting position and scale are considered as the coarse prediction, around which proposals for fine location are sampled according to Gaussian distribution. Because regions that are closer to the coarse location always owns the higher probability of target existence, more proposals need to be sample there. Meanwhile, the further away should also be covered with a small number of bounding boxes.

### 3.2 ASN for fine target localization

Based on the coarse state of the target estimated by the DCF module, we intend to perform a precise prediction by capturing the latent relations between the given template image and the current target. The majority of existing methods work by extracting features from both the template image and the search region, and the place with the highest feature similarity provides the hint for the target location. However, inspired by the prior investigations of [Valmadre et al. 2017], [Wang et al. 2018b], we construct an attentional siamese network, in which an attention subnet learns the channel weights of the features concerned and an estimation subnet utilizes the refined feature maps to predict the score of a certain proposal. Finally, among various candidate proposals, the one with the largest score indicates the fine location estimated from the ASN. The components of each subnet are shown in Figure 5.
Figure 3: Proposed ASN for fine localization. The first frame with a given ground truth in sequence is considered as the template image while the proposal boxes in the search region of the current frame are sampled under the guidance of DCF result. The backbone in each subnet is based on a pre-trained Resnet-50 (with feature maps extracted from Res-block3 and Res-block4). The Xception blocks in the proposed framework are of the same structure as that given in [Chollet 2017], and GAP represents the Global Average Pooling operation. The ⊗ symbol means element-wise product between the current feature maps and the corresponding channel weights produced by the attention subnet.

**Attention Subnet** This subnet starts with a backbone that extracts two feature maps of different depths from the template image. Each feature map is refined by a simple channel attention block followed by a classical Xception block with its dimensionality reduced to a quarter of the input. Then, the Precise ROI Pooling is utilized to compress the spatial size of the feature maps. A 1x1 pooling operates on the smaller feature map, while a 3x3 spatial pooling and a 3x3 convolution are sequentially introduced together on the larger feature map to avoid the loss of local details. After that, the two resulting feature vectors are fused and convoluted by two 1x1 convolutional filters to generate the channel weights.

**Estimate Subnet** Sharing the same backbone with the attention subnet, the estimate subnet owns a channel attention block as well. What is different is that the two Xception blocks are contained within each branch of the estimate subnet and the Precise ROI Pooling operators here reduce the spatial size of two feature maps to 3x3 and 5x5, respectively. Subsequently, features in different channels are re-weighted and the resulting features are transformed to vectors through GAP and 1x1 convolution, the two refined feature vectors are concatenated and fed into an FC-layer to predict the final confidence score of each proposal.

**Training and Loss Function** In order to train the proposed ASN, we apply the mean-squared error (MSE) loss function $L_{ASN}$ for accurate target state prediction, as in (3).

$$L_{ASN}(P_{gt}, P_{mn}, Score_{mn}) = \|GIOU(P_{gt}, P_{mn}) - Score_{mn}\|^2 \quad (3)$$

where $Score_{mn}$, $P_{mn}$ denote the $n$–th prediction output and proposal box in frame $m$, representatively. $P_{gt}$ means the given ground truth and the GIOU [Rezatofighi et al. 2019] represents the generalized intersection over union between two boxes.

Particularly, the template and search image are sampled from the training sequences with a maximum gap of 50 frames. For each image pair, we generate 16 candidate proposal boxes by adding Gaussian noise to the ground truth coordinates, while ensuring a minimum GIoU of 0.1. The MSE between the predicted score and the true computed GIOU is optimized using ADAM [Danelljan et al. 2017].
4 Experiments

In this section, the proposed DCF-ASN approach is evaluated and compared with SOTA tracking algorithms on thousands of challenging image sequences obtained from five popular visual tracking datasets: OTB100 [Wu et al. 2015], VOT2018 [Kristan et al. 2018], LaSOT [Fan et al. 2019], GOT-10k [Huang et al. 2019a], and TrackingNet [Muller et al. 2018]. All evaluation criteria are according to the original protocol defined in the five benchmarks respectively.

4.1 Implementation Details

The proposed DCF-ASN tracker is implemented in Python under the Pytorch framework. The proposed ASN is trained on the training subset of the corresponding datasets (LaSOT, GOT-10K, TrackingNet) with 128 frames per batch. During the training process, the training parameters in ASN are set to be the same as those in ATOM. All experiments of each tracker are carried out on a workstation with an Intel Xeon E5-2699 processor (2.30GHz) and NVIDIA 1080ti GPU.

4.2 State-of-the-art Comparison

For comparative studies on the five tracking benchmarks, we evaluate the proposed algorithm with SOTA trackers, including BACF [Kiani Galoogahi et al. 2017], STRCF [Li et al. 2018], MCCT [Wang et al. 2018a], SiamFC [Bertinetto et al. 2016b], ECO [Danelljan et al. 2017], CFNet [Valmadre et al. 2017], SiamFC-tri [Dong and Shen 2018], VITAL [Song et al. 2018], SiamRPN++ [Li et al. 2019], SiamMask [Wang et al. 2019], ATOM [Danelljan et al. 2019], and DiMP [Bhat et al. 2019].

| Method      | Backbone    | OTB100     | VOT2018    |
|-------------|-------------|------------|------------|
|             |             | AUC        | Pr         | EAO         | Acc         | FPS         |
| BACF        | -           | 0.597      | 0.810      | -           | -           | 10          |
| STRCF       | -           | 0.524      | 0.722      | -           | -           | 20          |
| MCCT        | VGGNet      | 0.673      | 0.898      | 0.393       | 0.580       | 2           |
| SiamFC      | AlexNet     | 0.560      | 0.747      | 0.188       | 0.503       | 122         |
| ECO         | VGGNet      | 0.659      | 0.892      | 0.280       | 0.484       | 28          |
| SiamFC-tri  | AlexNet     | 0.576      | 0.765      | -           | -           | 67          |
| VITAL       | -           | 0.678      | 0.910      | -           | -           | 3           |
| SiamRPN++   | ResNet50    | 0.692      | 0.907      | 0.415       | 0.600       | 15          |
| SiamMask    | ResNet50    | 0.643      | 0.832      | 0.380       | 0.610       | 24          |
| ATOM        | ResNet18    | 0.659      | 0.869      | 0.401       | 0.590       | 30          |
| DiMP        | ResNet50    | 0.683      | 0.892      | 0.440       | 0.597       | 40          |
| DCF-ASN     | ResNet50    | 0.684      | 0.906      | 0.450       | 0.612       | 38          |

Table 1: Comparisons with state-of-the-art methods on the OTB100 and VOT2018 datasets. AUC: area under curve; Pr: precision; EAO: expected average overlap; Acc: accuracy; FPS: frame per second. The first and second score are marked with red and blue respectively.

OTB100 and VOT2018 The OTB100 dataset consists of 100 challenging videos fully annotated with 11 different attributes. Based on the overlap precision (Pr) and area-under-the-curve (AUC) metrics, we validate the proposed DCF-ASN and other SOTA methods. As shown in Table 1, the proposed algorithm, integrating an efficient correlation filter with an attentional siamese model, achieves competitive results on both AUC and Pr. It is obvious that the proposed DCF-ASN (which incorporates the merits of DCF module and efficient attentional siamese network) runs at about 38 FPS on a single GPU, outdistribing the real-time requirement for practical applications.
VOT2018 is a widely-used supervised evaluation metric for visual object tracking, containing 60 sequences with various challenging factors. It is annotated with the rotated bounding boxes, and a re-initialized methodology is applied for evaluation. In particular, the VOT2018 benchmark measures the trackers in terms of accuracy (Acc), robustness (R), and expected average overlap (EAO). In this subsection, we compare the proposed method with the SOTA trackers reported in the VOT2018 Challenge. Table 1 shows that our tracker achieves the best performance in terms of EAO while maintaining a very competitive accuracy and speed. Although SiamMask utilizes much larger training data (including VOS dataset), our tracker can still outperform it.

LaSOT  The LaSOT dataset is a large-scale tracking dataset, consisting of 1400 sequences with average length of 2512 frames. It covers 70 object categories, in which each categorie contains 20 different sequences.

To provide a comprehensive evaluation, we have experimented on the testing subset with 280 videos, showing AUC in the success plot and Pr in the precision plot in Figure 4. In the success plot, the proposed tracker achieves the second best with a score of 0.565, only 1.4% separated from the best algorithm DiMP (0.579), while significantly outperforming the third method SiamRPN++ (0.496) with siamese structure by approximately 7%. Furthermore, DCF-ASN gains the highest score of 0.580 in the precision plot, having an advantage of 0.3% over the second best tracker DiMP (0.577) and a distinct advantage of 9.1% over the third method ATOM (0.489).

TrackingNet  As the largest wild object tracking dataset, TrackingNet assembles a total of over 30k video. All the 14,431,266 frames extracted from the 140 hours of visual content are annotated with a single upright bounding box. Coping with a large variety of frame rates, resolutions, context and object classes, 30,132 videos are selected as training dates and 511 videos with a distribution similar to the training set are utilized to test trackers. Algorithms evaluated on the TrackingNet are ranked according to AUC, precision (Pr) and normalized precision (NPr).

|            | ECO  | SiamFC | CFNet | MDNet | ATOM | SiamRPN++ | DiMP  | DCF-ASN |
|------------|------|--------|-------|-------|------|-----------|-------|---------|
| Pr         | 0.492| 0.533  | 0.533 | 0.565 | 0.648| 0.694     | 0.687 | 0.689   |
| NPr        | 0.618| 0.666  | 0.654 | 0.705 | 0.771| 0.800     | 0.801 | 0.803   |
| AUC        | 0.554| 0.571  | 0.578 | 0.606 | 0.703| 0.733     | 0.740 | 0.734   |

Table 2: State-of-the-art comparison on the TrackingNet dataset in terms of Pr, NPr and AUC.

As reported in Table 2, the proposed DCF-ASN achieves favorable performance compared to SOTA trackers. Although DCF-ASN witnesses a mere difference of 0.5% in Pr from the winner achieved by SiamRPN++, our method can run almost as three times faster as it.

Compared with the DiMP [Bhat et al. 2019] that is also built on the basis of the ATOM tracker, the results of our proposed method are still competitive. Notably, DiMP changes nothing on the target estimation network of ATOM, but increases the model size to 364MB owing to the improvement of the target classification module. However, for our
DCF-ASN, due to the introduction of correlation filter for rough estimation, its overall parameter number is only about 211 MB, which is approximately half of that of DiMP.

|        | MDNet | BACF | ECO | CFNet | SiamFC | ATOM | DiMP | DCF-ASN |
|--------|-------|------|-----|-------|--------|------|------|---------|
| $SR_{0.5}$ | 0.303 | 0.262 | 0.309 | 0.265 | 0.353 | 0.701 | 0.717 | 0.720   |
| $SR_{0.75}$ | 0.099 | 0.101 | 0.111 | 0.087 | 0.098 | 0.479 | 0.492 | 0.496   |
| $AO$     | 0.299 | 0.260 | 0.316 | 0.293 | 0.348 | 0.602 | 0.611 | 0.612   |

Table 3: State-of-the-art comparison on the GOT-10k dataset in terms of $SR_{0.5}$, $SR_{0.75}$ and $AO$.

**GOT-10k**  GOT-10k is a high-diversity dataset including 10k video sequences, where targets annotated frame-by-frame with bounding boxes. Our tracker are evaluated on the test subset, which contains 84 different object classes and 32 motion patterns. Trackers evaluated on test set will be reported at three metrics, the average overlap ($AO$) and success rates based on two overlap thresholds 0.5 ($SR_{0.5}$) and 0.75 ($SR_{0.75}$).

Table 3 illustrates that DCF-ASN achieves the top-ranked results in both AO (average overlap) and SR (success rate), including $SR_{0.5}$ and $SR_{0.75}$. Compared against the existing leading methods ATOM and DiMP for example, DCF-ASN makes an improvement of 1.7% and 0.4% respectively, in terms of $SR_{0.75}$, while also improving in $AO$ and $SR_{0.5}$.

### 4.3 Ablation Study

Figure 5 illustrates the ablation analysis on LaSOT dataset in terms of AUC and Pr. Counterparts without channel attention block, GIOU, Xception block are DCF-ASN/Attention, DCF-ASN/GIOU and DCF-ASN/Xception, respectively.

In this part of the experimental study, we perform an extensive ablation analysis to demonstrate the impact of each component in the proposed method, further illustrating its superiority.

As shown in Figure 5, the performance of DCF-ASN declines in varying degrees when different functional modules are removed. It indicates that all unique designs play an essential role in ASN. In particular, the introduction of the Xception block increases the use efficiency of the model parameters with a multiple branch structure, thereby increasing the accuracy. For the design of the attention module, we have also tried to apply Dual Attention [Fu et al. 2019] and Criss-Cross Attention [Huang et al. 2019b] to capture the long range dependencies between pixels. However, the experimental results are even not so good as those attainable by the simple channel attention structure. Perhaps under the current framework, the global contextual information does not contribute much to the tracking task. In addition, experimental results also prove that GIOU are more powerful than the traditional IOU when calculating loss within the proposed framework, and this may inspire further investigation in the future.

Note that we separate DCF and ASN from the proposed DCF-ASN and test them on the LaSOT dataset. The results are shown in Figure 5. Thanks to the learning process over large amounts of data, the AUC and Pr of ASN are higher than those of DCF. Nonetheless, the performance of DCF and ASN alone are much worse than that of DCF-ASN. Replacing
Figure 6: Ablation results on LaSOT dataset in terms of AUC and Pr. DCF-ASN, DCF, ASN counterparts using backbone Resnet-18, Resnet-50 and Resnet-101 are respectively DCF-ASN(DCF, ASN)\_18, DCF-ASN(DCF, ASN)\_50 and DCF-ASN(DCF, ASN)\_101.

the backbone with deeper CNN (Resnet-101) does not help to enhance the performance of the proposed method, whilst introducing more parameters.

Figure 7: Success and Precision plots of the proposed DCF-ASN and SOTA methods on the UA V123 dataset, with AUC and Precision(Pr) explicitly marked in plots.

4.4 Evaluation under Aerial Scenario

To further validate the generalization ability of the proposed tracker, we evaluated it in challenging aerial scenes, and compared it with representative tracking approaches on the typical datasets UA V123 [Mueller et al., 2016] and UAVDT [Du et al., 2018]. In addition to the general SOTA algorithms, ARCF [Dai et al., 2019], a tracker designed specifically for aerial scenarios, has also been added in this comparative study.

Evaluation on UAV123 Dataset  UAV123 is a popular aerial video-based tracking dataset that consists of 123 video sequences, of which 115 are produced by a UAV platform and 8 are created using UAV simulation software. UAV123 contains kinds of scenarios, such as fields, streets, cities, suburbs, oceans and so on. The dataset embodies a total of 12 attributes: Aspect Ratio Change, Background Clutter, Camera Motion, Fast Motion, Full Occlusion, Illumination Variation, Low Resolution, Out-of-View, Partial Occlusion, Similar Object, Scale Variation and Viewpoint Change. Each sequence carries several of them.

The success and precision plots on the UAV123 dataset are shown in Figure 7, while the further attribute based evaluation results are presented in Table 4 and 5. Overall, DCF-ASN achieves the highest score of 0.868 and 0.654 on both Pr and AUC among approaches compared. The experimental results indicate that the proposed method are able to estimate the target state in complex aerial scenarios with balanced accuracy and speed.
Figure 8: Success and Precision plots of the proposed DCF-ASN and SOTA methods on the UAVDT dataset, with AUC and Precision(Pr) explicitly marked in plots.

Table 4: Attribute based evaluation results. AUC(%) of DCF-ASN and state-of-the-art trackers on different attributes in the UA V123 dataset. The first, second and third highest values are highlighted in color.

| Attribute                | DCF-ASN | DiMP | ATOM | SiamRPN++ | SiamMask | TADT | ARCF | VITAL | ECO | MCCT | STRCF |
|--------------------------|---------|------|------|-----------|----------|------|------|-------|-----|------|-------|
| Scale Variation          | 64.2    | 62.3 | 61.1 | 62.3      | 58.2     | 50.6 | 44.2 | 50.6  | 49.4| 47.2 | 44.6  |
| Aspect Ratio Change      | 62.2    | 62.0 | 59.9 | 61.4      | 56.3     | 47.4 | 41.6 | 47.4  | 45.4| 44.5 | 39.6  |
| Low Resolution           | 51.6    | 48.7 | 46.7 | 45.4      | 42.4     | 37.2 | 33.9 | 37.2  | 37.6| 35.6 | 34.1  |
| Fast Motion              | 61.4    | 61.2 | 59.9 | 58.1      | 54.0     | 41.9 | 34.0 | 41.9  | 43.1| 40.3 | 34.2  |
| Full Occlusion           | 45.0    | 44.8 | 40.2 | 42.5      | 34.0     | 29.8 | 23.6 | 29.8  | 29.8| 28.6 | 23.8  |
| Partial Occlusion        | 59.7    | 58.1 | 57.0 | 56.3      | 50.8     | 47.0 | 39.5 | 47.0  | 44.7| 44.3 | 39.7  |
| Out-of-view              | 60.8    | 59.6 | 58.6 | 56.0      | 56.7     | 46.6 | 39.6 | 46.6  | 43.8| 43.1 | 38.4  |
| Background Clutter       | 48.6    | 48.0 | 47.2 | 44.8      | 36.9     | 41.1 | 33.8 | 41.1  | 41.1| 40.3 | 31.6  |
| Illumination Variation   | 61.0    | 63.0 | 63.1 | 60.7      | 53.7     | 49.6 | 39.9 | 49.6  | 45.9| 47.8 | 36.7  |
| Viewpoint Change         | 65.8    | 64.8 | 64.8 | 68.2      | 62.6     | 50.4 | 41.8 | 50.4  | 48.6| 46.2 | 40.8  |
| Camera Motion            | 66.3    | 65.6 | 65.2 | 65.8      | 60.6     | 53.6 | 45.4 | 53.6  | 49.9| 50.1 | 46.5  |
| Similar Object           | 63.1    | 62.4 | 61.0 | 59.0      | 53.9     | 49.7 | 46.0 | 49.7  | 47.7| 47.3 | 44.4  |

Table 5: Attribute based evaluation results. Pr(%) of DCF-ASN and state-of-the-art trackers on different attributes in the UA V123 dataset. The first, second and third highest values are highlighted in color.

| Attribute                | DCF-ASN | DiMP | ATOM | SiamRPN++ | SiamMask | TADT | ARCF | VITAL | ECO | MCCT | STRCF |
|--------------------------|---------|------|------|-----------|----------|------|------|-------|-----|------|-------|
| Scale Variation          | 84.2    | 83.0 | 82.8 | 82.0      | 76.9     | 69.2 | 64.0 | 71.3  | 71.3| 69.8 | 64.0  |
| Aspect Ratio Change      | 82.8    | 83.3 | 82.2 | 81.8      | 75.8     | 66.4 | 61.3 | 68.8  | 67.9| 67.9 | 58.5  |
| Low Resolution           | 75.9    | 73.3 | 72.6 | 69.0      | 63.8     | 67.7 | 57.0 | 63.5  | 64.5| 63.3 | 59.7  |
| Fast Motion              | 85.0    | 83.2 | 82.5 | 77.4      | 73.3     | 61.0 | 50.5 | 63.6  | 67.2| 63.6 | 56.2  |
| Full Occlusion           | 67.1    | 70.3 | 66.7 | 66.1      | 54.7     | 60.5 | 45.3 | 55.9  | 56.1| 54.8 | 45.3  |
| Partial Occlusion        | 81.0    | 80.2 | 80.2 | 77.1      | 70.2     | 69.0 | 57.6 | 68.9  | 66.9| 67.3 | 58.2  |
| Out-of-view              | 80.6    | 79.9 | 79.4 | 81.6      | 76.2     | 60.9 | 54.0 | 66.3  | 62.0| 62.2 | 53.3  |
| Background Clutter       | 65.1    | 71.1 | 70.9 | 65.5      | 55.7     | 68.3 | 56.0 | 63.9  | 59.9| 62.5 | 50.2  |
| Illumination Variation   | 83.1    | 85.6 | 87.2 | 81.5      | 73.6     | 66.9 | 60.7 | 73.1  | 71.6| 73.3 | 55.5  |
| Viewpoint Change         | 84.7    | 83.7 | 84.9 | 87.6      | 81.5     | 65.2 | 60.8 | 69.9  | 71.2| 67.7 | 59.0  |
| Camera Motion            | 88.1    | 86.7 | 86.9 | 86.3      | 79.9     | 71.4 | 64.2 | 74.3  | 70.7| 71.6 | 65.3  |
| Similar Object           | 81.1    | 83.7 | 85.0 | 80.0      | 71.6     | 72.2 | 68.0 | 70.5  | 71.3| 71.8 | 63.1  |
Evaluation on UAVDT Dataset  
UAVDT is a recent created aerial video dataset that includes three fundamental tasks, i.e., object detection, single object tracking and multiple object tracking. Here, we utilize the test set of the single object tracking part (50 video sequences). It mainly contains various common scenes of urban district such as squares, arterial streets, toll station, highways, crossings and T-junctions. The video sequences in this dataset are annotated with 9 attributes, that is: Background Clutter, Camera Rotation, Object Rotation, Small Object, Illumination Variation, Object Blur, Scale Variation, Large Occlusion and Long-term Tracking. Notably, about 74% of video sequences are annotated with at least 4 attributes.

Table 6: Attribute based evaluation results. AUC(%) of DCF-ASN and state-of-the-art trackers on different attributes in the UAVDT dataset.

| Attribute                  | DCF-ASN | DiMP   | ATOM   | SiamRPN++ | SiamMask | TADT   | ARCF   | VITAL  | ECO    | MCCT   | STRCF  |
|----------------------------|---------|--------|--------|-----------|----------|--------|--------|--------|--------|--------|--------|
| Camera Motion              | 61.5    | 57.8   | 58.9   | 59.4      | 57.9     | 41.7   | 44.9   | 41.9   | 41.9   | 40.9   | 41.3   |
| Object Motion              | 60.8    | 56.0   | 56.7   | 59.4      | 57.9     | 38.2   | 41.7   | 40.9   | 38.2   | 39.2   | 38.6   |
| Small Object               | 57.2    | 56.4   | 57.2   | 59.2      | 60.9     | 44.5   | 49.2   | 44.8   | 44.0   | 45.0   | 45.0   |
| Illumination Variations    | 61.3    | 58.8   | 58.8   | 66.4      | 63.4     | 44.4   | 47.8   | 48.7   | 44.6   | 47.4   | 47.8   |
| Object Blur                | 59.3    | 54.9   | 55.1   | 65.8      | 61.8     | 43.2   | 46.8   | 46.1   | 43.4   | 46.4   | 45.8   |
| Scale Variations           | 63.4    | 58.3   | 60.3   | 60.1      | 58.5     | 43.2   | 43.7   | 43.6   | 40.7   | 41.0   | 41.4   |
| Long-term Tracking         | 72.4    | 70.5   | 70.4   | 65.1      | 70.7     | 52.9   | 57.9   | 55.3   | 55.3   | 60.3   | 60.8   |
| Background Clutter         | 56.1    | 52.5   | 52.9   | 54.7      | 52.3     | 40.1   | 41.4   | 39.0   | 36.1   | 38.3   | 37.5   |
| Large Occlusion            | 55.2    | 55.6   | 55.6   | 49.8      | 46.0     | 39.4   | 38.7   | 36.7   | 34.2   | 33.1   | 32.8   |

Figure 8 presents the comparison results of the proposed DCF-ASN and aforementioned preeminent algorithms on the UAVDT datasets. Obviously, our DCF-ASN method gains the first in terms of precision and AUC with the score 83.7% and 61.4%, respectively. As reported in Table 6 and 7, the proposed approach always ranks top-3 on all challenging attributes, which proves its robustness and accuracy.

Table 7: Attribute based evaluation results. Pr(%) of DCF-ASN and state-of-the-art trackers on different attributes in the UAVDT dataset.

| Attribute                  | DCF-ASN | DiMP   | ATOM   | SiamRPN++ | SiamMask | TADT   | ARCF   | VITAL  | ECO    | MCCT   | STRCF  |
|----------------------------|---------|--------|--------|-----------|----------|--------|--------|--------|--------|--------|--------|
| Camera Motion              | 84.0    | 79.0   | 80.0   | 75.9      | 76.7     | 64.7   | 71.5   | 70.4   | 67.3   | 65.2   | 64.5   |
| Object Motion              | 82.6    | 77.3   | 77.5   | 80.4      | 77.8     | 62.5   | 66.7   | 62.7   | 60.8   | 60.2   | 60.4   |
| Small Object               | 86.5    | 81.5   | 83.3   | 83.5      | 86.7     | 81.6   | 84.8   | 81.4   | 80.1   | 80.4   | 78.5   |
| Illumination Variations    | 84.5    | 81.7   | 82.2   | 89.7      | 86.4     | 76.1   | 79.6   | 82.4   | 77.1   | 77.9   | 77.5   |
| Object Blur                | 82.7    | 75.9   | 77.6   | 89.4      | 86.0     | 74.4   | 75.9   | 75.9   | 75.3   | 75.9   | 74.5   |
| Scale Variations           | 82.4    | 77.7   | 78.4   | 80.1      | 77.3     | 61.0   | 64.2   | 65.3   | 60.5   | 59.0   | 58.0   |
| Long-term Tracking         | 97.0    | 99.9   | 97.2   | 84.9      | 93.8     | 97.4   | 86.3   | 90.7   | 89.1   | 98.6   | 93.9   |
| Background Clutter         | 76.6    | 73.5   | 72.2   | 74.9      | 71.6     | 66.0   | 66.7   | 67.5   | 59.9   | 58.9   | 59.1   |
| Large Occlusion            | 70.5    | 72.3   | 72.2   | 66.6      | 60.2     | 52.8   | 54.8   | 52.7   | 48.5   | 41.2   | 42.9   |

As illustrated in Tables 4-7, DCF-ASN performs well when the camera is fast moving or the object suffers from motion blur, benefitting from the proposed "coarse-to-fine" strategy. The DCF sub-module enables dense sampling around the peak of response map, while less proposals are generated on the positions with a low response value. Thus, the ASN sub-module can make multiple confirmations in the region where the target is most likely to appear. Even if the target scale changes drastically, this coarse-to-fine strategy could help ensure the robust tracking performance. Both the conventional DCF based algorithms (e.g. ECO) and the popular CNN-based trackers (e.g. DiMP) cannot perform well alone when such challenges exist.

4.5 Analyses on Performance and Model Size

In order to test the efficiency of model parameters usage, comparisons regarding the relationships between performance and model size are done on the large-scale general tracking dataset LaSOT and typical aerial tracking dataset UAV123. Results are shown in Figure 9. Our DCF-ASN achieves competing AUC and Pr on two datasets, having a better tradeoff between performance and model size. Although the number of parameters employed by VITAL is much smaller than that used by others, it can only run at about 3 FPS. The compression of model size is achieved at the cost of reducing speed, which limits the application of VITAL. Compared with DiMP, our tracker performs better in most cases with less parameters. This indicates that DCF-ASN utilises parameters with high-efficiency, and therefore is more memory efficient.
4.6 Qualitative evaluation

To evaluate the performance of the proposed DCF-ASN more comprehensively, we have selected the representative DCF tracker (ECO), the siamense algorithms (SiamRPN++), and the competitive SOTA method (ATOM) to conduct a qualitative analysis on the sequences in different scenarios.

As shown in Figure 10, ATOM, though including components for target estimation and classification, cannot generate an accurate bounding box. ECO, constantly updated online, suffers from serious model drift and thus loses the precise location and scale of the target. SiamRPN++, an offline-trained generative tracker, lacks of ability of adopting to the target appearance variation and hence, fails under this circumstance. The proposed DCF-ASN, combining the unique strengths of traditional DCF and siamense tracker, thereby achieving the best tracking accuracy overall.

5 Conclusion

This paper has presented a novel coarse-to-fine visual tracking framework, which consists of an online-updating DCF module and an offline-training attentional siamese network (ASN). The proposed ASN is an asymmetric network that can learn to capture the coefficient of different channels from the template and weigh the features of the search region. By integrating a standard DCF with the ASN efficiently, the proposed approach achieves favorable tracking accuracy while holding its real-time ability. Comprehensive experiments on five large-scale datasets have systematically demonstrated the superior performance of this tracking framework. In the future, tensor decomposition techniques may be introduced to reduce the computational burden and speed up the tracker further. Meanwhile, we will continue to improve the precision of bounding box regression by exploiting the advanced anchor-free technique in tracking.
Figure 10: Qualitative demonstration of proposed DCF-ASN and representative state-of-the-art (SOTA) trackers on sequences Diving and Car16 obtained from datasets OTB100 and UAV123.

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