Correlation-Aware Deep Tracking

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Abstract

Robustness and discrimination power are two fundamental requirements in visual object tracking. In most tracking paradigms, we find that the features extracted by the popular Siamese-like networks cannot fully discriminatively model the tracked targets and distractor objects, hindering them from simultaneously meeting these two requirements. While most methods focus on designing robust correlation operations, we propose a novel target-dependent feature network inspired by the self-/cross-attention scheme. In contrast to the Siamese-like feature extraction, our network deeply embeds cross-image feature correlation in multiple layers of the feature network. By extensively matching the features of the two images through multiple layers, it is able to suppress non-target features, resulting in instance-varying feature extraction. The output features of the search image can be directly used for predicting target locations without extra correlation step. Moreover, our model can be flexibly pre-trained on abundant unpaired images, leading to notably faster convergence than the existing methods. Extensive experiments show our method achieves the state-of-the-art results while running at real-time. Our feature networks also can be applied to existing tracking pipelines seamlessly to raise the tracking performance.

1. Introduction

Visual object tracking (VOT) is a long-standing topic in computer vision. There are two fundamental yet competing goals in VOT: on one hand, it needs to recognize the target undergoing large appearance variations; on the other hand, it needs to filter out the distractors in the background which may be very similar to the target.

Most appearance-based approaches address this challenge in two perspectives: the first is to learn a more expressive feature embedding space by Siamese-like extraction network [22, 58]; the second is to develop a more robust correlation operation, such as Siamese cropping [23, 58], online filter learning [3, 18] and Transformer-based fusion [5, 50]. Since the modern backbones [17, 34] become the mainstream choice in deep era, most trackers devote to the correlation operation, hoping to discriminate targets from distractors given their features. Despite their great success, few of these tracking paradigms notice that the two competing goals may put the feature network into a target-distractor dilemma, bringing much difficulties to the correlation step. The underlying reasons are three folds: 1) The Siamese encoding process is unaware of the template and search images, which weakens the instance-level discrimination of learned embeddings. 2) There is no explicit modelling for the backbone to learn the decision boundary that separates the two competing goals, leading to a sub-optimal embedding space. 3) Each training video only annotates one single object while arbitrary objects including distractors can be tracked during inference. This gap is further enlarged by 2). Our key insight is that feature extraction should have dynamic instance-varying behaviors to generate "appropriate"
embeddings for VOT to ease the dilemma. In more details, it needs to generate coherent features for the same object in all frames of a video in spite of the variations; on the other hand, it needs to generate contrasting features for the target and distractors with similar appearance.

To this end, we present a novel dynamic feature network on top of the attention scheme [37]. As shown in Fig. 2 (a2), our Single Branch Transformer (SBT) network allows the features of the two images to deeply interact with each other at the stage of feature extraction. Intuitively, the cross-attention weights gradually filter out target-irrelevant features layer by layer while the self-attention weights enrich the feature representations for better matching. Thus, the feature extraction process is target-dependent and asymmetrical for image pair, allowing the network to achieve a win-win scenario: it differentiates the target from similar distractors while preserving the coherent characteristics among dissimilar targets. The effectiveness of features from SBT is validated in Fig. 2 (d2). The features belonging to the target (green) become more and more separated from the background (pink) and distractors (blue) while the search features from Siamese extraction are totally target-unaware.

The overall framework of SBT is shown in Fig. 3. It has three model stages on top of Extract-or-Correlation (EoC) blocks. The patch embedding produces embeddings for the template and search images. Then the embeddings are fed to the stacked EoC blocks. There are two variants of EoC, i.e., EoC-SA and EoC-CA, which use Self-Attention (SA) and Cross-Attention (CA) as its core operator, respectively. The EoC-SA block fuses features within the same image while the EoC-CA block mixes features across images. The output features of the search image are directly fed to the prediction heads to obtain a spatial score map and a size embedding map. Our key technical innovation is introducing one single stream for template and search image pair processing that jointly extract or correlate through homogeneous attention-based blocks. Thus, SBT can be pre-trained on abundant unpaired images such as ImageNet [33], leading to a fast convergence in the fine-tune on tracking.

Extensive experiments are conducted to compare different SBT network designs. Based on the insights, we summarize a number of general principals. Our method achieves superior performance and improves Siamese, DCF and Transformer-based trackers as can be seen in Fig. 1. The main contributions of this work are as follows:

• We present a novel tracking framework which allows the features of the search and template image to be deeply fused for tracking. It further improves existing popular tracking pipelines. To our best, we are the first to propose a specialized target-dependent feature network for VOT.

• We conduct a systematic study on SBT tracking both experimentally and theoretically, and summarize several general principles for following works.

The rest of the paper is organized as follows. We discuss related work in Sec. 2. The SBT framework is presented in Sec. 3. Then, we conduct empirical studies and theoretical analysis on SBT in Sec. 4 and Sec. 5, respectively. Finally, we provide extensive experimental results in Sec. 6 and conclude the paper in Sec. 7.

2. Related Work

Visual Tracking. The Siamese network [2] based trackers have drawn great attention in recent years. By introducing the powerful backbones [22, 58] and elaborated prediction networks [16, 23, 49], Siamese trackers obtain superior performance. However, the offline target matching with a shallow correlation structure [2] lacks of discriminative power towards distractors. Then, the dedicated modifications rise, including attention mechanism [15, 41, 54], online module [59, 61], cascaded frameworks [7, 14, 39], update mechanism [55] and target-aware model fine-tuning [24, 38]. Despite the improvements, most of them bring much complexity to the Siamese tracking pipeline. Instead, our target-dependent feature network can upgrade the original network seamlessly. Moreover, our feature network formulates a novel and conceptually simple tracking pipeline by removing the separated correlation step in Siamese trackers.

Discriminative Correlation Filter (DCF) tracker [18] learns a target model by solving least-squares based regression online. It is further improved by fast gradient algorithm [11], end-to-end learning [3, 60] and CNN-based size
3. Architecture

This section introduces the overall architecture of our Single Branch Transformer (SBT) (Fig. 3) as well as its main building block (EoC block). Then, in the next section, we evaluate a number of instantiations of the architecture followed by a summary of favorable design principals.

3.1. Patch Embedding

Our model takes two images as input, comprising a template image \( z \in \mathbb{R}^{3 \times H_z \times W_z} \) and a larger search image \( x \in \mathbb{R}^{3 \times H_x \times W_x} \). In general, \( z \) is centered on the target object while \( x \) represents a larger region in the subsequent frame which contains the target. In the Patch Embedding (PaE) stage, the two images are fed to a convolutional layer \( \varphi_f^0 \) with kernel size \( 7 \times 7 \) and stride 4, followed by a layer normalization (LN) layer. It embeds the images into feature maps of \( f_z^0 \) and \( f_x^0 \), respectively,

\[
f_z^0, f_x^0 = \text{LN}(\varphi_f^0(z)), \quad \text{LN}(\varphi_f^0(x)),
\]

where \( f_z^0 \in \mathbb{R}^{C_0 \times \frac{H_z}{4} \times \frac{W_z}{4}} \), \( f_x^0 \in \mathbb{R}^{C_0 \times \frac{H_x}{4} \times \frac{W_x}{4}} \) and \( C_0 \) is the number of channels.

3.2. Extract-or-Correlation Block

EoC block which can simultaneously implement Self-Attention (SA) and Cross-Attention (CA) is the main building block. Intuitively, they gradually fuse features from the same and different images, respectively. It is known that computing attention globally among all tokens leads to quadratic complexity [26]. To address this, there are a number of works which attempt to reduce the computation cost. We present a general formulation for different efficient attention methods. On top of the formulation, we describe our SA and CA operations.

Let \( \chi(\cdot) \) denote a function that reshapes/arranges a feature maps into the desired form. The function varies for different methods. We compute the \( q, k, v \) features as:

\[
q_i = [\chi_q(f_i)]^T \omega_q, \quad i \in \{z, x\}, \\
k_i = [\chi_k(f_i)]^T \omega_k, \quad i \in \{z, x\}, \\
v_i = [\chi_v(f_i)]^T \omega_v, \quad i \in \{z, x\},
\]

where \( \{\omega_q, \omega_k, \omega_v\} \) represent linear projections.

The Vanilla Global attention (VG) [12] computes attention among all tokens. So \( \{\chi_q, \chi_k, \chi_v\} \) represent identity mapping. The Spatial-Reduction Global attention (SRG) [43, 56] uses a convolution with a stride larger than one (i.e. \( \{\chi_k, \chi_v\} \)) to reduce the spatial resolution of the
key and value features. The resolution of the query features is not changed. Then it computes global attention as VG. The method largely reduces the computational overhead. The Vanilla Local window attention (VL) \cite{26} splits feature tokens in groups based on their spatial locations and only computes attention within each group. Swin Transformer \cite{26} further adds a Shift window mechanism to vanilla Local attention (SL) for global modelling.

Since the target object may appear anywhere in the search image, it is not practical to use local attention methods for CA. In our work, we use SRG to implement SA and CA. More discussions are in Sec. 4. The following equation shows how we compute SA or CA:

\[
\tilde{f}_{ij} = \text{Softmax}(\frac{q_i k_j^T}{\sqrt{d_h}}) v_j, \quad i, j \in \{z, x\},
\]

In SA, \(i\) and \(j\) are from the same source (either \(z\) or \(x\)) and the resulting feature update is:

\[
f_z := f_z + \tilde{f}_{zz}, \quad f_x := f_x + \tilde{f}_{xx},
\]

In CA, it mixes the features from different sources:

\[
f_z := f_z + \tilde{f}_{zz}, \quad f_x := f_x + \tilde{f}_{xx}.
\]

We can see that the correlation between the two images is deeply embedded in feature extraction seamlessly. EoC block also consists of two LN layers and a 2-layer MLP as shown in Fig 3 (b).

### 3.3. Position Encoding

For majority methods \cite{4, 12, 26}, the encoding is generated by the sinusoidal functions with Absolute coordinates (Abs) or Relative distances (Rel) between tokens. Being much simpler, Conditional positional encoding \cite{9, 43, 56} (Cond) generates dynamic encoding by convolutional layers. In our model, we add a \(3 \times 3\) depth-wise convolutional layer \(\varphi_{pe}\) to MLP before GELU as conditional PE.

### 3.4. Direct Prediction

Different from the existing tracking methods, we directly add a classification head \(\Phi_{cls}\) and regression head \(\Phi_{reg}\) on top of the search feature \(\hat{f}_z\) from SBT \(\Omega\) without additional correlation operations:

\[
\hat{f}_z = \Omega(z, x), \quad y_{reg} = \Phi_{reg}(\hat{f}_z), \quad y_{cls} = \Phi_{cls}(\hat{f}_z),
\]

where \(y_{reg}, y_{cls}\) denote the target regression and classification results to estimate the location and shape of the target.

We implement \(\Phi_{reg}\) and \(\Phi_{cls}\) by stacking multiple Mix-MLP Blocks (MMB) which can jointly model the dependency between the spatial and channel dimensions of the input features \(f^{i-1}\) in the \(i^{th}\) MMB:

\[
\hat{f}^i = \varphi_{sp}(\text{RS}(\varphi_{cn}(\text{RS}(f^{i-1})))),
\]

where \(\varphi_{sp}\) and \(\varphi_{cn}\) consist of a linear layer followed by RELU activation. RS represents reshape. \(\varphi_{cn}\) is applied to features along the channel dimension, and the weights are shared for all spatial locations. In contrast, the operator \(\varphi_{sp}\) is shared for all channels.

### 4. Empirical Study of SBT Instantiations

In this section\(^1\), we conduct empirical studies on SBT variants by raising a number of questions.

As efficient attention computing is vital to the SBT, we firstly ablate other network factors including hierarchical structure, position encoding and patch embedding. As shown in Tab. 1, it is obvious that hierarchical structure performs much better than single stage because of multi-scale representation (A1 Vs. A2 to A7). Conditional PE only surpasses the relative PE by 0.4 points (A5 Vs. A6). The difference between PE methods is rather small, indicating that PE does not have key impacts on performance. We also

\(^1\)All the experiments follow the official GOT-10k \cite{19} test protocol.
find that convolutional PaE is more practical and expressive than hand-crafted patch merging ($A_3$ vs. $A_5$).

**Which attention computation is better for SBT tracker?** The main difference between attention computation lies in the operation to reduce complexity (global/local attention). We find that local attention (VL/SL) block cannot directly perform Cross-Attention as the inequality of local windows in template and search image. Thus, for SBT constructed by pure local attention blocks, we adopt same image size ($224 \times 224$) for template/search image ($A_2$) to avoid tedious hand-crafted cross strategies. Comparing to the settings with global attention block (VG/SRG) ($A_3$ to $A_7$) which adopt $128 \times 128$ as template size, the performance of pure local attention ($A_2$) drop at least 3.6 points in $AO$ with more parameters and flops. *This is mainly due to the negative impacts of over background information in template which may confuse the search branch.* We also investigate the mix setting of SRG and VL block ($A_7$). To be specific, the VL block is for Self-Attention while SRG block is for Cross-Attention. We observe that the pure SRG block design achieves the better performance ($A_3$ vs. $A_7$). This illustrates that *SBT benefits from unified block choice.* $A_3$ also validates the effectiveness of pure SRG blocks with 63.7% in $AO$. We conclude that *pure SRG block is more practical and efficient for SBT tracker.*

**Do earlier and more EoC-CA blocks help to tracking better?** With a baseline designed from above principles, it strikes to us that SBT may benefit from earlier and more cross correlation. We ablate different position/number of EoC-CA block in Fig. 4. As shown in Fig. 4 (d), when the number of EoC-CA blocks increases, the performance of model rises consistently with the same EoC-SA/EoC-CA position pattern ($C_3$ vs. $C_4$, $C_1$ vs. $C_2$, $C_6$ vs. $C_9$). It proves that *SBT tracker benefits from more comprehensive Cross-Attention between template and search branch.* In Fig. 4 (d), when the number of EoC-CA block is the same, earlier cross design has significant positive impacts ($C_4$ surpasses $C_1$ by 4.9 points, $C_6$ surpasses $C_2$ by 6.5 points). The underlying reason is that *early-cross generates target-dependent features which help tracker to see better.*

**Is tracking performance related to the placement pattern of EoC-CA blocks?** As the position and number of EoC-CA block have significant impacts on performance, it comes to us which pattern of placement is the optimal choice. So we make attempts to place EoC-SA/EoC-CA block differently. In Fig. 4 (f), we surprisingly find that interleaved EoC-SA/EoC-CA pipeline performs better than the separation pattern even with less Cross-Attention and latter earliest cross position ($C_3$ vs. $C_1$). The potential cause is that *EoC-SA block can refine the template/search feature after the correlation, resulting in a more expressive feature space for matching.* In Fig. 4 (f), model ($C_9$) achieves the best performance 67.2% when the interval is 1. When the interval increases to 2, the performances drops from 61.1% to 59.2% ($C_3$ vs. $C_{10}$). Thus, we prefer an interleaved EoC-SA/EoC-CA block design for SBT tracker.

**What is the optimal network variants for tracking model?** Then, it comes to us a long-standing problem for designing a deep tracker. We ablate different network stride, model stage and model size. As shown in Tab. 1, over parameters and flops in shallow level (stage 1 and 2) is harmful. It is mainly because the low dimension cannot formulate informative representations (57.4 of $B_2$ vs. 60.6 of $B_6$). We also observe that increasing the head number slightly improves the performance but decreases the speed. *With the same total network stride, three-stage model performs better than four-stage model (63.5 of $B_2$ vs. 57.4 of $B_2$) with comparable parameters and flops. Though setting the network stride to 16 can reduce the flops, the performance drops 11.3 points ($B_1$ vs. $B_7$), indicating that SBT tracker prefers larger spatial size of features.* As the channel dimensions influence model size a lot, it is vital to achieve a balance between block numbers and channel dimensions (56.7 of $B_3$ vs. 63.3 of $B_3$).

**Does flexible design of EoC-SA/EoC-CA bring negative/positive effects?** We examine the potential negative/
positive effects in SBT. From Fig. 4 (b) and Fig. 4 (c), we observe that early-cross in shallow-level (stage 1 and 2) does not bring much improvements ($C_2$ vs. $C_8$, $C_6$ vs. $C_7$) but lowers the inference speed. It is because the early-cross destroys the one-shot inference. The shallow-level EoC-SA blocks perform as buffer. So the trade-off between early-cross and speed should be well-considered.

In Fig. 4 (e), SBT tracker benefits from more pre-trained weights and converges much faster than Transformer-based trackers, such as TransT [5] and STARK [50].

5. Single Branch Transformer Driven Tracking

Beyond exploring SBT experimentally, we theoretically analyze SBT from the perspective of general VOT. Then, we analyze SBT from the perspective of general VOT.

5.1. Theoretical Analysis on SBT for Tracking

SBT overcomes the intrinsic restrictions in deep trackers. Deep trackers have an intrinsic requirement for strict translation invariance, $f (c, x \Delta T_j) = f (c, x) \Delta T_j$ where $\Delta T_j$ is the shift window operator. $c$ denotes the template/online filter in Siamese/DCF tracking and $f$ denotes correlation operation. Modern backbones [17, 48] can provide more expressive features while their padding is inevitable to destroy the translation invariance. Thus, deep trackers [22, 58] crop out padding-affected features and adopt spatial-aware sampling training strategy to keep the translation invariance. Theoretically, padding in SBT can be removed completely or only exists in patch embedding for easy implementation. Moreover, the flattened feature tokens has permutation invariance which makes EoC block completely translation invariance. As the EoC block provides global receptive field, SBT can enjoy arbitrary size of template/search image and larger search area scale. Thus, we argue that SBT driven tracking can overcome the intrinsic restrictions in classical deep trackers theoretically by using brand-new network modules.

Cross-Attention is more than twice as effective as depth-wise correlation. We first prove that Cross-Attention can be decomposed into dynamic convolutions (D-Conv). CA which performs as feature correlation is mathematically equivalent to two D-Conv and a SoftMax layer. For simplicity, we annotate the encoded $\{q, k, v\}$ features to their original feature as the projection matrix is $1 \times 1$ position-wise convolutional filters. So the CA for query from search feature $x$ to template feature $z$ is:

$$\text{Inter} = \text{RS}(z)^T x + 0 = W_1(z)^T x + b_1,$$

$$\text{Attn}_{xz} = \text{Softmax}(\text{Inter}),$$

$$\tilde{f}_{xz} = \text{Attn}_{xz} z + x = W_2(z, x)^T x + b_2(x),$$

where $W(a, b), b(a, b)$ is the weight matrix and bias vector $a, b$ and RS denotes reshape. To obtain the correlation feature $f_{xz}$, the search feature $x$ goes through a D-Conv layer generated by $z$, a SoftMax layer and another D-Conv layer generated by $z$ and $x$. Two D-Conv layers come from the reshape of $z$ along channel and spatial dimension. The depth-wise correlation (DW-Corr) or pixel-wise correlation (Pix-Corr) [51] is only equivalent to one D-Conv layer. Thus, CA is twice as effective as DW-Corr or Pix-Corr with the same template feature as dynamic parameters.

Hierarchical feature utilization is embedded in serial pipeline. Siamese trackers [6, 22] perform correlation for each hand-selected feature pair and feed them into parallel prediction heads. Then, prediction results are aggregated by a weighted sum. Comparing to the hand-craft layer-wise aggregation, SBT structure explores multi-level feature correlation intrinsically. We take three-level feature utilization as an example:

$$x_1, z_1 = \phi_{ca}^i(\bar{x}_i, \bar{z}_i), \quad i \in \{0, 1, 2\}$$

$$x_2, z_2 = \phi_{ca}^i(\phi_{ca}^0(\phi_{ca}^0(x_0, z_0))),$$

$$S_{sbt} = \varphi(x_2),$$

where $\{0, 1, 2\}$ represents shallow, intermediate and deep level. $\{\bar{x}, \bar{z}\}$ are the previous layer features of $\{x, z\}$, $\phi_{ca}^i, \varphi$ denote EoC-CA block and prediction head.

Though in a serial pipeline, the prediction result $S_{sbt}$ naturally contains hierarchical feature correlation results.

5.2. Four Versions of SBT network

Following the guidelines from Sec. 4, our four versions of SBT is described in Tab. 2. For pre-training, we add extra fourth model stage and modify the network stride as [26]. For fine-tune on tracking, we only use three-stage model and replace the prediction head.
Table 3. Comparison on the GOT-10k [20] test set.

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Table 5. Results on VOT2020. We use AlphaRefine [51] to generate mask for VOT benchmark.

Table 6. Comparison on the TrackingNet test set.

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Table 7. Improvements of CATs over baselines on GOT-10k [19] and DAVIS17 [31] benchmarks. \( \frac{J}{F} \) denotes the mean of the region similarity/contour accuracy.

Figure 5. Comparisons on (a) OTB-100 [45] and (b) GOT-10K [19] test set in terms of success plot.

Testing. For SBT/Siamese, we adopt fixed template as [46]. For DCF/STM, the inputs are firstly fused with template by SBT.

6.2. Comparison to State-of-the-Art Trackers

GOT-10K. GOT-10K [19] is a large-scale benchmark which has the zero overlap of object classes between training and testing. We follow the official policy without extra training data. As shown in Tab. 3 and Fig. 5, in a fair comparison scenario, our base and large version outperform other top-performing trackers such as STARK-st101, TransT, TrSiam, and DiMP, verifying the strong generalization to unseen objects. Our light and small version also achieve competitive results with much smaller size.

OTB100/VOT2020/LaSOT. We refer the reader to [13, 21, 45] for detailed descriptions of datasets. In challenging short-term benchmarks (VOT2020 and OTB100), Tab. 5 shows that SBT-small achieves competitive result, which is better than SuperDiMP. After increasing the model variants, SBT-base obtains an EAO of 0.515, being superior to other top-performing trackers. With a much simpler pipeline, our SBT-large is even closed to the winner of VOT2020 challenge RPT [28] (0.530 EAO). Fig. 5 shows our base and large version achieves sota results in OTB. In long-term benchmark LaSOT, with the comparable model size and no online update, SBT-base outperforms the recent strong Transformer-based methods (STARK-st50 and TransT).

6.3. Improvement over Baselines

Box-Level tracking. In Tab. 7, our correlation-aware features improve other tracking pipelines with comparable model size and less computation burden.

Pixel-Level tracking. In multi-object video object segmentation (VOS) benchmark DAVIS17 [31], STM-CA im-
Table 8. Ablation studies on GOT-10k [19]. S3B6 denotes the third stage 6th block. Fea.Ext denotes the feature extraction network. Corr.Emd denotes whether network embeds correlation into extraction layers. Fea.Corr denotes the feature correlation method. For DCF, we integrate SBT-base to ECO [10].

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<td>S3</td>
<td>S4</td>
<td>56.2</td>
<td></td>
</tr>
<tr>
<td>② ResNet-50</td>
<td>×</td>
<td>CA</td>
<td>S2</td>
<td>S3</td>
<td>S4</td>
<td>57.5</td>
<td></td>
</tr>
<tr>
<td>③ ResNet-50</td>
<td>×</td>
<td>DCPI</td>
<td>S2</td>
<td>S3</td>
<td>S4</td>
<td>30.3</td>
<td></td>
</tr>
<tr>
<td>④ SBT-base</td>
<td>×</td>
<td>DW-Corr</td>
<td>S3B6</td>
<td>S3BB</td>
<td>S3B10</td>
<td>60.1 (3.9+)</td>
<td></td>
</tr>
<tr>
<td>⑤ SBT-base</td>
<td>×</td>
<td>CA</td>
<td>S3B6</td>
<td>S3BB</td>
<td>S3B10</td>
<td>61.5 (4.0+)</td>
<td></td>
</tr>
<tr>
<td>⑥ SBT-base</td>
<td>×</td>
<td>DCF</td>
<td>S3B6</td>
<td>S3B10</td>
<td>31.5 (1.2+)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>⑦ SBT-base</td>
<td>✓</td>
<td>DW-Corr</td>
<td>S3B6</td>
<td>S3BB</td>
<td>S3B10</td>
<td>65.0 (3.5%/7.5%)</td>
<td></td>
</tr>
<tr>
<td>⑧ SBT-base</td>
<td>✓</td>
<td>DCF</td>
<td>S3B6</td>
<td>S3BB</td>
<td>S3B10</td>
<td>65.9 (4.8%/9.7%)</td>
<td></td>
</tr>
<tr>
<td>⑨ SBT-base</td>
<td>✓</td>
<td>DCF</td>
<td>S3B6</td>
<td>S3BB</td>
<td>S3B10</td>
<td>35.2 (3.7%/4.9%)</td>
<td></td>
</tr>
</tbody>
</table>

Figure 6. (a), (b), (c) denote three trackers (refer to Sec. 6.4). The first sub-figure indicates the average true positive rate and average negative numbers of negative objects. The other sub-figures denote the T-SNE and classification maps.

proves STM by 3.6% in terms of $J$, proving that VOS methods can benefit from our discriminative embeddings.

6.4. Exploration Study

We further explore the characteristics of our SBT feature by training it on the GOT-10k [19] training split.

Correlation-embedded structure. As shown in Tab. 8, correlation-embedded SBT (④, ⑧, ⑨) significantly improves the tracking performance on all correlation cases (④, ⑤, ⑨). Comparing to the layer-wise aggregation, correlation-embedded trackers outperform the CNN-based trackers or attention-based trackers (65.9% of ⑨ Vs. 60.1% of ④, 65.0% of ⑤ Vs. 61.5% of ⑧, 39.2% of ⑨ Vs. 30.3% of ③). It clearly verifies that SBT structure is more effective on multi-level feature utilization. We also prove that CA works better than DW-Corr in feature correlation (60.1% of ④ Vs. 61.5% of ⑧). Fig. 7 also shows the superiority of correlation-embedded structure.

Target-dependent feature embedding. We further explore the features of three different settings in two folds: one is to maintain spatial location information while another is to classify the target from distractor objects. We begin by training three models withCls head only to localize the target: (a) Correlation-embedded tracker. (b) Siamese correlation with SBT. (c) Siamese correlation with ResNet-50.

We select the five hard videos from OTB [44] benchmark. The search image randomly jitters around target. We only evaluate the Cls map for localization. In Fig. 6, the true positive rate of target ground-truth indicates that (a), (b) can preserve more spatial information than CNN (c). The T-SNE/Cls map also show the target-dependent characteristic of (a) features. The average negative objects (largest connected components) of (a) is higher than (b) which indicates that correlation-embedded is critical to filter out distractors.

Benefits from pre-training. Comparing to the existing trackers [5, 46, 50], our tracking model except prediction heads can be directly benefit from the ImageNet [33] pre-trained weights. As shown in Fig. 8 (a), there is a significant correlation between the number of pre-trained blocks and tracking performance. We also investigate the impacts of model variants of SBT. In Fig. 8 (b), the SBT tracking model prefers consistent block numbers for pre-training. We also observe that SBT converges faster and the stabilized IoU value rises with more pre-trained model weights.

7. Conclusion

In this work, we are the first to propose a target-dependent feature network for VOT. Our SBT greatly simplifies the tracking pipeline and converges much faster than recent Transformer-based trackers. Then, we conduct a systematic study on SBT tracking both experimentally and theoretically. Extensive experiments demonstrate that our method achieves sota results and can be applied to other tracking pipelines as dynamic feature network.

Acknowledgment

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