Robust Visual Object Tracking with Natural Language Region Proposal Network

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Abstract

Tracking with natural-language (NL) specification is a powerful new paradigm to yield trackers that initialize without a manually-specified bounding box, stay on target in spite of occlusions, and auto-recover when diverged. These advantages stem in part from visual appearance and NL having distinct and complementary invariance properties. However, realizing these advantages is technically challenging: the two modalities have incompatible representations. In this paper, we present the first practical and competitive solution to the challenge of tracking with NL specification. Our first novelty is an NL region proposal network (NL-RPN) that transforms an NL description into a convolutional kernel and shares the search branch with siamese trackers; the combined network can be trained end-to-end. Secondly, we propose a novel formulation to represent the history of past visual exemplars and use those exemplars to automatically reset the tracker together with our NL-RPN. Empirical results over tracking benchmarks with NL annotations demonstrate the effectiveness of our approach.

1 Introduction

“A picture is worth a thousand words” goes an old adage. Thus, a typical approach to tracking requires a “picture” called an exemplar to initialize tracking [7, 12, 26]. Even tracking methods that self-initialize via a proposal mechanism, be it motion-detection or a class-specific detector, use the proposal to obtain a “picture” of the object to be tracked.

As new applications of computer-vision gain prominence, the validity of that old adage becomes less obvious. Broadly, these new applications are unified by an idea of “AI you can talk to.” In this paper, we develop a new formulation, in effect betting that “a few words are worth a thousand pixels.” We opt for a natural-language (NL) description of the target.

However, conditioning a tracker on NL description is not straightforward. First, since tracking implies temporal coherence, applying an algorithm for matching text to image regions [37, 40] for each video frame independently would not yield competitive results in challenging scenarios. Second, it is not obvious how to derive a formulation to combine the strengths of appearance-based tracking with the language modality. Indeed, the best published attempts [13, 26] did not fare well compared to the state-of-the-art in visual tracking benchmarks. In this paper, we propose a natural language region proposal network (NL-RPN) to perform tracking by NL description.

In contrast with prior NL-tracking work, we exploit a siamese tracking by detection architecture. However, past siamese trackers [24, 25, 35] have modeled little or no temporal variations of targets [15]. Therefore, we propose a memory management mechanism (MMM) algorithm, which is implemented as a state machine [39] to update the visual exemplar of the target and thereby enable siamese trackers to capture the temporal variations of the target.
As a result of the proposed NL-RPN and MMM algorithm, we build a tracker that is able to recover from model drift by automatically resetting itself using the NL description of the target. An example of such a recovery is shown in Fig. 1.

Contributions of this paper include the following:

- A novel natural language region proposal network (NL-RPN) that performs tracking by consuming video sequence and a natural-language description of the target to be tracked. Specifically, this is the first siamese correlation filter based tracker that consumes NL instead of region templates.

- We propose a Memory Management Mechanism (MMM) for tracking, which not only handles the visual exemplar updates used in the proposed tracker, but also makes online decisions about tracking state transitions as well. The MMM makes it possible to restore the proposed tracker based on its own history of decisions. Compared to past siamese trackers, our tracker is more robust in recovering from occlusions and target losses.

- The proposed NL-RPN is end-to-end trained offline with large scale training set of image sentence pairs. Experiments on visual object tracking benchmarks that are annotated with NL shows that our tracker is more robust in terms of recovering from occlusions and target losses.

2 Related Works

2.1 Tracking

In the past two decades, tracking by detection models [3, 20] and Bayesian filtering based algorithms [4, 21] have been thoroughly studied in the field of visual object tracking. Some deep learning based models [2, 7, 30, 34] have been introduced in recent years, and are argued to perform better when handling occlusion and appearance change. ECO [7] applies convolutional filters on convolution feature maps to obtain satisfactory performance on multiple tracking datasets. ECO still suffers from efficiency issues [17], though its efficiency is improved from the original convolution filter based tracker, C-COT [8]. These trackers maintain appearance and motion models explicitly by maintaining the visual features over time. SiamFC [2] conducts a local search for regions with a similar regional visual features obtained by a CNN in every frame. SiamRPN [25] and SiamRPN++ [24] performs tracking as one shot detection using the siamese network as a region proposal network. However, these siamese trackers do not model the temporal appearance variations of the target and have model drift problems.

2.2 Language Understanding in Vision Tasks

In the last decade, researchers start to look into exploiting natural language understanding in vision tasks. These models usually consist of two components: a language model and an appearance model to learn a new feature space that is shared between both NL and appearance [19, 36]. Li et al. define two tracking by natural language specification problems [26]. Feng et al. formalize the tracking by natural language in a tracking by detection framework with Bayesian detection formulation [13]. However, in their work, an assumption that appearances and the natural language description be conditional independent given the bounding boxes is made. By directly measuring this joint conditional probability, we derive a fully convolutional neural network (CNN) that performs tracking by natural language description. Similar to that of Li et al.’s work [25], we formulate the tracking with natural language description problem as one-shot detection.

3 Natural Language Region Proposal Network (NL-RPN)

Following [13] and [35], let \( I_t \) denote the frame from a sequence at time step \( t \), and let \( Q \) be the NL description of the target. Variables and functions used in deriving the proposed tracker are summarized in Table 1. Rather than assume conditional independence between target appearance and \( Q \) given the ground truth bounding box [13], we propose a Natural Language Region Proposal Network (NL-RPN), which estimates the conditional probability \( \Pr [A_t | X_t, Q] \), where \( A_t \) is a set of anchor boxes and \( X_t \) represents the search patch at time step \( t \).

The overall architecture of our model is presented in Fig. 2. The NL-RPN takes NL description of the target and performs detection on the search patch, while the Siamese Region Proposal Network (SiamRPN) [25] takes a visual exemplar and performs detection on the same search patch. Both RPNs share the same backbone CNN, which makes the proposed model fully convolutional and therefore compatible with past siamese trackers, in particular, our model can be combined with SiamRPN and trained jointly end-to-end.

In this section, we describe our proposed one-shot detection model using NL description of the target. We present our tracker using this one-shot detection model later in Sec. 4.

3.1 Architecture of NL-RPN

The architecture of the NL-RPN is shown in the top half of Fig. 2. We designed the NL-RPN to be fully convolutional and compatible with siamese trackers.

As is common practice, the NL description \( Q \) is transformed into an embedding using a sentence embedding model [1, 5, 31] pretrained on a text corpus. Our novelty is the follow-on transformation from this sentence embedding into an NL kernel denoted by \( Z_Q \). We follow by a \( 1 \times 1 \) convolution layers, denoted as \( \phi_{\text{cls}} \) and \( \phi_{\text{reg}} \). These convolutional layers, \( \phi_{\text{cls}} \) and \( \phi_{\text{reg}} \), turn \( Z_Q \) into a tensor compatible with \( X_t \) for the depth-wise cross correlation layer to estimate the target score and regression for all anchor boxes:

\[
\begin{align*}
A_{\psi, \text{cls}} &= v_{\text{cls}}(\psi(X_t)) \ast \phi_{\text{cls}}(Z_Q); \\
A_{\psi, \text{reg}} &= v_{\text{reg}}(\psi(X_t)) \ast \phi_{\text{reg}}(Z_Q),
\end{align*}
\]
where \( \psi_{\text{cls}} \) and \( \psi_{\text{reg}} \) are multiple 1 \times 1 convolution layers with batch normalization on the convolutional feature map of \( X_t \). The tensor \( A^\chi_{Q,\text{cls}} \) have a shape of \( w \times h \times 2k \) and \( A^\chi_{Q,\text{reg}} \) have a shape of \( w \times h \times 4k \), where \( w, h \) are width and height of the convolution feature map and \( k \) is the number of anchors. We consider Eq. 1 as an estimation of probabilities for anchor boxes: \( \Pr[A_t | X_t, Q] \).

Furthermore, if visual exemplars are available for our proposed tracker, a SiamRPN [24] based detector, shown in the bottom half of Fig. 2, is utilized to further assist the NL-RPN. Let \( Z = \{Z_{t_1}, \cdots, Z_{t_M}\} \) be a set of visual exemplars of the target at earlier time steps seen by the tracker, i.e., \( t_1, \cdots, t_M < t \). The siamese CNN \( \psi \) is used to extract appearance features from these visual exemplars. Additional convolutional layers together with batch normalization, \( \psi_{\text{cls}} \) and \( \psi_{\text{reg}} \) are finally used to estimate the joint probability \( \Pr[A_t | X_t, Z_{t_i}] \) for each visual exemplar \( Z_{t_i} \in Z \):

\[
\begin{align*}
A^\chi_{t_i,\text{cls}} &= \psi_{\text{cls},x}(\psi(X_t)) \ast \psi_{\text{cls},z}(\psi(Z_{t_i})) ; \\
A^\chi_{t_i,\text{reg}} &= \psi_{\text{reg},x}(\psi(X_t)) \ast \psi_{\text{reg},z}(\psi(Z_{t_i})).
\end{align*}
\]

We describe how to use both the NL-RPN and the SiamRPN with \( Z \) to perform tracking in Sec. 4.

### 3.2 Loss Functions and Training

As the proposed NL-RPN is fully convolutional and shares the same backbone with the SiamRPN, the NL-RPN can be trained either jointly with the SiamRPN or it can be trained after the SiamRPN is trained, both in a end-to-end fashion. To construct training instances that resemble the test-time distribution, we randomly choose two frames at different time steps, \( I_t \) and \( I_{t_j} \), together with the corresponding ground truth bounding boxes \( B^*_t \) and \( B^*_j \). We crop and resize \( Z_{t_i} \) (on \( I_{t_i} \)) for the visual exemplar, and \( X_{t_j} \) (on \( I_{t_j} \)) for the search patch. Thus, a triplet \((Z_{t_i}, X_{t_j}, Q)\), is constructed as the input for training our proposed tracker.

Similar to the training process of the RPN in Faster R-CNN [14], we sample 16 anchors that have an intersection over union (IoU) with \( B^*_t \) greater than 0.7 as positive anchors and another 48 anchors that have an IoU less than 0.3 as negative anchors. We use a softmax cross entropy loss for training classification branches and a smoothed L1-loss for training regression branches in both the NL-RPN and the SiamRPN.

### 4 Tracking with NL-RPN

In this section, we will discuss how to use a trained NL-RPN to perform tracking with NL description. Alg. 1 shows the proposed tracking algorithm.
Using the average optical flow $\mathbf{v}$ after obtaining the search patch $X_t$.

Figure 3: With the help with optical flow for motion guidance, a better sampling strategy for $X_t$ gives NL-RPN and Siamese RPN a higher chance of making the correct prediction.

for an initial bounding box $\hat{B}_1$ with highest prediction confidence from NL-RPN given the scale of the target.

### 4.2 Sampling $X_t$ with Optical Flow Guidance

It has become standard practice to adopt a constant position motion model and to search for the target in a new frame $I_t$ in a region centered at the previous predicted location $\hat{B}_{t-1}$. However, such search strategy is sub-optimal as it ignores both the target’s motion and the global scene motion. As is shown in Fig. 3, this sampling strategy would end up with target loss and would make neither the NL-RPN nor the SiamRPN able to make correct detection.

Therefore, we use the average optical flow within $\hat{B}_{t-1}$ predicted by FlowNet 2 [18] as guidance for cropping $X_t$ from $I_t$. Following the guidance of the motion, $X_t$ is cropped on the center of $\hat{B}_{t-1}$ adding the average optical flow $\mathbf{v}$.

### 4.3 Detection with NL-RPN and SiamRPN

After obtaining the search patch $X_t$, we run an inference pass of the proposed model to obtain $\hat{A}_t^{Z,cls}$, $\hat{A}_t^{Z,reg}$, $\hat{A}_t^{Q,cls}$, and $\hat{A}_t^{Q,reg}$. In practice, when tracking with multiple visual exemplars, our tracker choose the visual exemplar with the highest positive score for any anchor for making inference:

$$\hat{A}_t^{Z,cls} = \hat{A}_t^{Z,cls}, \quad \hat{A}_t^{Z,reg} = \hat{A}_t^{Z,reg},$$

where $\hat{Z}_t = \text{arg max}_{Z \in \mathbb{Z}} \left( \max_{w,h,k} \sigma \left( \hat{A}_t^{Z,cls}(w,h,k) \right) \right)$, $\sigma$ is the function that applies the softmax activation and extracts the value for the foreground class.

By resizing $\hat{A}_t^{Z,cls}$, $\hat{A}_t^{Q,cls}$ and applying the regression, we get a set of bounding boxes and scores proposed by the SiamRPN and the NL-RPN denoted as $S_t^Z, B_t^Z$ and $S_t^Q, B_t^Q$ respectively:

$$S_t^Z \doteq \sigma \left( \hat{A}_t^{Z,cls} \right), S_t^Q \doteq \sigma \left( \hat{A}_t^{Q,cls} \right);$$

$$B_t^Z \doteq \text{Box Regression} \left( \hat{A}_t^{Z,reg} \right);$$

$$B_t^Q \doteq \text{Box Regression} \left( \hat{A}_t^{Q,reg} \right).$$

A sub-window attention function, $g$, with a 2D-Gaussian function centered at $X_t$ is used to boost scores of anchors near the center of $X_t$ and reduce scores of anchors distant from the center of $X_t$. Therefore, for both SiamRPN and NL-RPN, we choose the bounding box with the highest score:

$$\hat{S}_t^Z = \left( S_t^Z \right)_m;$$

$$\hat{S}_t^Q = \left( S_t^Q \right)_n;$$

$$\hat{B}_t^Z = \left( B_t^Z \right)_m;$$

$$\hat{B}_t^Q = \left( B_t^Q \right)_n;$$

$$m = \text{arg max}_{S_m \in S_t^Z} g(S_m), \quad n = \text{arg max}_{S_n \in S_t^Q} g(S_n).$$

### 4.4 Memory Management Mechanism (MMM)

The proposed Memory Management Mechanism (MMM) is designed for extra robustness of the proposed tracker. There are two major functionalities of the MMM: 1) Capture the temporal appearance variation of the target in Memory $\mathbb{Z}$; 2) Determine the state of tracking, denoted as $\chi$. MMM is presented in Alg. 2, and the transition of tracking state $\chi$ is shown in Fig. 4.

**Initialize $\mathbb{Z}$**: We first initialize $\mathbb{Z}$ from either a ground truth bounding box $B_t^*$ or an estimation $\hat{B}_t$ from $Q$ as described in Sec. 4.4.1. Afterwards, at time step $t$, when an inference is made, either from the NL-RPN or the SiamRPN, the predicted bounding box $\hat{B}_t$ is
Algorithm 1: The proposed tracker.

Input : $I_1, \ldots, I_T, \hat{Z}_Q$, and optionally $B^*_1$.
if $B^*_1$ is given then
  $\hat{B}_1 = B^*_1$
else
  $\hat{B}_1 = \text{Multi-scale sliding window search from NL-RPN with } Z_Q$ and $I_1$
end

Initialize $\mathcal{Z} = \{Z_1\}$
State $\chi = \text{STABLE}$
for $t = 2$ to $T$ do
  Sample $X_t$ with Optical Flow Guidance
  // Make Prediction Following Eq. 5.
  if $\chi \neq \text{CONTINUED LOST}$ then
    $\hat{S}_t, \hat{B}_t = \text{SiamRPN}(X_t, \hat{Z})$
  else
    $\hat{S}_t, \hat{B}_t = \text{NL-RPN}(X_t, Z_Q)$
  end
  // Run MMM algorithm as in Alg. 2.
  $\chi_t, Z = \text{MMM}(\{\hat{S}_1, \ldots, \hat{S}_t\}, \hat{B}_t)$
end

Output: $\hat{B}_1, \ldots, \hat{B}_T$.

used to sample a new visual exemplar $Z_t$ and add it to the memory of the tracker $\mathcal{Z}$ if certain criteria are met.

**Updating $\mathcal{Z}$ by Reverse Nearest Neighbor:** Intuitively, we wish to only add confident predictions into the memory. However, having redundant visual exemplars not only slows down the tracker, but also makes the tracker become biased and eventually drift away from the target. Therefore, we adopt the reverse nearest neighbor algorithm [22, 32] and add $Z_t$ to $\mathcal{Z}$ if the reverse nearest neighbor set of $Z_t$ with $\mathcal{Z}$ is an empty set. The rationale is that we add $Z_t$ to $\mathcal{Z}$ only if the new exemplar “looks” different to its past, and therefore the memory captures the temporal appearance variations of the target.

Each exemplar $Z_t$ is given an initial weight as $Z^w_t = 1.0$, when added to $\mathcal{Z}$. $Z^w_t$ will decrease if it does not achieve the highest score in Eq. 3 for every time step and will increase otherwise. Similar to the halving algorithm [28], if the weight becomes less than 0, the corresponding $Z_t$ will be removed from $\mathcal{Z}$.

In practice, in order to make the memory efficient, the proposed tracker only runs reverse nearest neighbor every $\Delta T = 50$ frames and only if the score $\hat{S}_t$ is higher than a threshold of $\tau_1 = 0.99$.

**Tracking State $\chi$:** With the history of decisions $\hat{S}_1, \ldots, \hat{S}_{t-1}$ made during inference, the proposed tracker makes a decision on which of the following four state it would be in: 1. Stable 2. Lost 3. Continued Lost 4. Restore The transition criteria of these four states are presented in Fig. 4. The tracking state transition is implemented as a rule based state machine, similar to that of Xiang et al.’s work [39].

**Stable** means that our tracker is confident about its decisions. **Lost** means that our tracker is not confident about its recent decisions,  *i.e.*, scores from immediate past $\hat{S}_t, \hat{S}_{t-1}, \hat{S}_{t-2}$ are lower than a threshold of $\tau_2$ and the target might have lost the search region $X_t$. Although this might be due to an appearance change or partial occlusion of the target, our tracker will rely on the NL-RPN for making decisions and the sub-window attention function $g$ is no longer used during inference.

However, if the model transits into the **Continued Lost** state, it means that the tracker has been suffering from a long-term lost of the target, *i.e.*, scores in a longer immediate past is lower than the threshold $\tau_2$. In this case, we restore the tracker to a historical state in the memory to handle scale changes of the target. Additionally, in order to handle appearance changes or occlusion for an extended period of time, we utilize the proposed NL-RPN to automatically “reset” the tracker, which will be discussed in details in Sec. 4.5. After the model is restored from **Continued Lost** state, it enters a state called **Restore**. If the proposed tracker is stable for a period of time, it will eventually get back to the **Stable** state. On the other hand, if the model starts to make low confident predictions in a
In this section, we conduct comprehensive experiments and ablation study comparing the performance of three variants of our proposed tracker with the strong baseline of SiamRPN++ [24] tracker.

5.3 Comparisons with Siamese Baseline

In this section, we first describe the datasets used in our experiments and show the effectiveness of our proposed NL-RPN and MMM by conducting a comprehensive set of ablation studies. Then, we compare our tracker with other state-of-the-art visual object trackers and past NL trackers.

5 Experiments

4.5 NL-RPN and SiamRPN Aggregation

The proposed NL-RPN is used to “reset” the tracker when the MMM determines that the model is in the Lost or Continued Lost state.

A naive approach to aggregate NL-RPN with SiamRPN would be a weighted sum following a similar mechanism from SiamRPN++ [24]. However, this is not well motivated, as the two modalities of visual appearance and natural language generate different kernels for the depth-wise cross correlation operation; indeed this approach does not fare well on our datasets.

Therefore, as discussed earlier, our proposed NL-RPN is used for only making decisions when our tracker enters the Lost or Continued Lost state. Our tracker performs an automatic reset by the NL-RPN with \( Q \) and \( X_t \) sampled on \( I_t \) with multiple scales (sizes) and locations based on visual exemplars \( Z \).

5.1 Datasets

5.1.1 Training Datasets

Our backbone ResNet [16] model is pretrained on ImageNet [9]. We use all images and phrases from VisualGenome [23], frames from MSCOCO [27] and YouTube-BoundingBox [33], together with images from training splits of LaSOT and lang-OTB-99 [26] for training the SiamRPN backbone and NL-RPN.

We choose to follow [24] to choose the size of \( 127 \times 127 \) pixels for \( Z_t \), and the size of \( 255 \times 255 \) pixels for \( X_t \) during training.

5.1.2 Evaluation Datasets

With the tracking by NL setup, we are aware of two publicly available tracking benchmarks that are annotated with NL for targets. In Li et al.’s early work on NL tracking [26], they annotated OTB-100 [38] with NL and end up with a Lingual OTB99 dataset. In a more recent work [11], LaSOT, a large single object tracking benchmark dataset annotated with NL for targets, is introduced with 70 different categories of objects and 20 sequences for each category, totaling at 1,400 sequences. We choose to follow the protocol 2 from the original publication, which is to evaluate our tracking by One Pass Evaluation (OPE) on the testing split of the dataset.

5.2 Implementation Details

5.2.1 Training Initialization

We initialize the stride-reduced ResNet [24] with pretrained weights on ImageNet [9] and randomly initialize layers in the SiamRPN following the original work [25]. Layers other than the sentence encoder in the proposed NL-RPN are initialized randomly to construct the NL kernel described in Sec. 3.1. The sentence encoder is implemented via a universal sentence encoder [6].

5.2.2 Learning Rates and Convergence

We train our proposed NL-RPN together with SiamRPN using a TensorFlow 2.0 implementation on 4 Nvidia Titan V GPUs with Adagrad [10] optimizer and an initial learning rate at 0.001. We decay the learning rate after 5 epochs to 0.0005 and continued training for another 5 epochs. Batch size is set to 16 per GPU for a total of 64 triplets of \( Z_t \), \( X_t \), and \( Q \) per batch. Gradients are averaged over each batch, while the gradients for NL-RPN are omitted if \( Q \) is not present. The proposed model takes about 2 days to converge using the loss described in Sec. 3.2.
Figure 5: Ablation studies on the OTB-99-language dataset using the OPE protocol. The Baseline is our re-implementation of SiamRPN++ [24]. NL-RPN+MMM+Flow is the full-fledged version of our tracker. NL-RPN+MMM and MMM+Flow are two simplified variants of our tracker, with the optical flow-guided sampling (Flow) component and the NL-RPN component removed respectively.

Figure 6: Comparison of our approach against state-of-the-art traditional trackers and NL trackers: AUC of success rate at different intersection over union thresholds and AUC of mean average precision at different location error thresholds on testing videos in LaSOT and OTB-99-lang.
Table 2: With the proposed NL-RPN and MMM, our tracker is able to recover from occlusions and target loss faster than other trackers on LaSOT [11].

OPE results on the OTB-99-language dataset are shown in Fig. 5.¹ The proposed new mechanisms, NL-RPN and MMM, effectively boost the tracking performance of the Siamese baseline by a large margin, and the adoption of optical flow-guided sampling strategy lead to further performance boost.

### 5.4 Comparisons with Other Trackers

We also compare our proposed model with the following state-of-the-art trackers: SiamRPN++ [24], SiamRPN [25], MDNet [29], VITAL [34], SiamFC [2], ECO [7], Li [26], and Feng [13]. For the fairness of comparison, we use their released codes, model weights, and hyper-parameters in all experiments.

In Fig. 6, we plot the success rate at different IoU thresholds and the precision at different location error thresholds on both LaSOT [11] and OTB-99-lang [26]. We also report the area under curve (AUC) for each plotted curve. In Fig. 6c and Fig. 6f, we follow Li et al. [26] to conduct experiments on OTB-lang-99 under two different setups for tracking with NL, i.e., tracking with NL only and initialization with both the bounding box and the NL description of the target. Overall, our tracker is competitive with state-of-the-art trackers and NL trackers.

Moreover, to validate the ability of our proposed tracker in recovering from occlusions and loss of target during tracking, we compute the following statistics from the OPE (starting from the first frame) on LaSOT: 1) Average IoU with ground truth bounding box on 100 consecutive frames after each full occlusion; 2) Average number of frames until a tracker is able to reacquire the target with an IoU greater than 0 after each full occlusion; and 3) Average number of frames until a tracker is able to reacquire the target with an IoU greater than 0 after each target loss (no intersection between prediction and ground truth). The results are summarized in Table 2. Our tracker is able to recover from occlusions and target losses faster than all competing trackers, which demonstrates the effectiveness and strength of the proposed NL-RPN and MMM.

### 6 Conclusion

We present a novel NL-RPN which performs tracking by consuming video sequence and an NL description of the target. Together with the proposed MMM for tracking, our tracker enjoys better robustness than other visual object trackers. Experiments on challenging datasets demonstrate that our tracker is better at handling occlusions and recovering from lost of targets than other state-of-the-art trackers and prior attempts on NL tracking.

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¹We re-implement the SiamRPN++ and train it from scratch. While we were not able to reproduce the performance of the released model (after hyper-parameter tuning), we use the same set of hyper-parameters for all variants of our tracker and thus enables a fair comparison between the baseline and our methods.
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