CoCoLoT: Combining Complementary Trackers in Long-Term Visual Tracking

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Abstract—How to combine the complementary capabilities of an ensemble of different algorithms has been of central interest in visual object tracking. A significant progress on such a problem has been achieved, but considering short-term tracking scenarios. Instead, long-term tracking settings have been substantially ignored by the solutions. In this paper, we explicitly consider long-term tracking scenarios and provide a framework, named CoCoLoT, that combines the characteristics of complementary visual trackers to achieve enhanced long-term tracking performance. CoCoLoT perceives whether the trackers are following the target object through an online learned deep verification model, and accordingly activates a decision policy which selects the best performing tracker as well as it corrects the performance of the failing one. The proposed methodology is evaluated extensively and the comparison with several other solutions reveals that it competes favourably with the state-of-the-art on the most popular long-term visual tracking benchmarks.

I. INTRODUCTION

Visual object tracking can be defined as the persistent recognition and localization of a target object in consecutive video frames. It is one of the fundamental open problems in computer vision and it has many practical applications such as video surveillance [1], behavior understanding [2], robotics [3], and medical image analysis [4].

Depending on the behavior of the target and the dynamics of the captured scene, a visual object tracking problem can be either divided into short-term tracking or long-term tracking [5]. The first scenario occurs when the target never leaves completely the camera’s field of view. This is the most popular setting represented in the community’s benchmark datasets [6], [7], [8], [9], [10] and subsequently the most tackled by solutions. Successful methodologies available today to address short-term scenarios include discriminative tracking [11], [12], [13], siamese networks [14], [15], [16], deep regression trackers [17], [18], [19], and transformers [20], [21], [22].

In the setting of long-term tracking problems the assumption of the target being always visible is relaxed. In such scenarios the object disappears by leaving the field of view or by being completely occluded by another object. These situations require a tracker to produce not only the target’s localization but also a confidence score expressing whether the object is visible or not [5]. In the past, long-term trackers [23], [24], [25], [26] consisted in variations of an essential scheme composed of: a short-term tracking algorithm to follow the target while visible; a re-detection operation to find again the target after its reappearance; a verification module to check if the short-term tracker and re-detector have localized the object of interest. More recently, the properties of such complex and often inefficient pipelines are starting to be achieved implicitly with compact deep neural network-based trackers. New visual trackers such as the deep discriminative tracker SuperDiMP [13], [27] and the transformer-based solution STARK [22] are able to match or even surpass the long-term tracking performance of previous methodologies while performing at real-time speed. Such efficiency makes the employment of tracker fusion strategies [28], [29], [30], [31] appealing since the processing speed of an ensemble-based solution could be reasonable. The latter approaches demonstrated how increased tracking performance can be achieved by the careful combination of the complementary capabilities of different trackers. However, the solutions available today focused on the fusion of trackers only in short-term scenarios and, to the best of our knowledge, yet no work explored such an approach for long-term visual object tracking.

In this paper, we try to fill such a gap by proposing a framework that aims to combine the capabilities of complementary trackers to enhance the tracking performance in long-term problems. The framework, named CoCoLoT (Combining Complementary Trackers in Long-Term Tracking), is conceptually different from the approaches currently available for long-term tracking, as visualized by Figure 1. Our strategy is based on a tracker evaluation function that determines if each
tracker is following correctly the target. The function maintains an online-learned representation of the target which allows discriminating the object of interest from the background. This peculiarity is used to assess whether the localization provided by the trackers includes the appearance of the target. The proposed evaluation strategy allows to select the best target localization among those proposed by the trackers regardless of their methodology or implementation. The outcome of the selection is exploited to make the trackers interact and correct their performance by themselves during tracking, ultimately achieving higher tracking robustness by merging their capabilities. Overall, the main contribution of this paper is the first demonstration of tracker fusion in the context of long-term visual object tracking. Through an extensive experimental campaign it will be demonstrated that CoCoLoT improves the performance of the underlying trackers by a good margin. In particular, we will show that the combination of two complementary tracking approaches achieves new state-of-the-art results on the most popular long-term tracking benchmarks LTB-50 [5], [7], TLP [32], and LaSOT [33]. CoCoLoT (aka mLP LT) won the VOT2021 Long-Term Challenge [34].

II. RELATED WORK

A. Long-Term Visual Tracking

Kalal et al. [23] considered the long-term tracking task under the fruitful framework of tracking, learning, and detection in which: a short-term tracker based on median-flows follows the target while visible; a learning module generates training examples during tracking for target recognition; and an online learned cascade classifier is used as target detector. Such a scheme has been then improved by many follow-up solutions [25], [26] which exploited deep learning models to implement the short-term tracker, the target verification module, or the detector. Differently from such approaches, the FuCoLoT tracker [35] extended the discriminative correlation filter (DCFs) approach [36] to the long-term setting by optimizing multiple filters at different time scales to implement a short-term tracker and a long-term detector which predictions are then fused together. The GlobalTrack tracker [37] made the deep siamese approach [14] work in long-term scenarios by searching the target globally instead of locally in each frame. More recently, the STARK tracker [22] exploited transformer neural networks [38] to implement an effective matching operation that is able to perform short-term tracking and re-detection at the same time.

Enlightened by the recent capabilities of trackers which achieve remarkable results in the long-term context without sacrificing efficiency [22], [13], [27], in this work we follow a different idea with respect to the aforementioned and propose a new framework for long-term tracking aiming to combine the characteristics of complementary tracker with an effective evaluation and interaction strategy.

B. Tracker Fusion Strategies

Different approaches have been proposed to fuse the execution of multiple trackers while tracking. Yoon et al. [28] made different trackers interact by exploiting a probabilistic approach based on particle filters. The MEEM tracker [39] later provided a multi-expert framework where trackers are fused via a procedure based on entropy minimization. Wang et al. [40] and Vojir et al. [30] used variations of Hidden Markov models to implicitly correct an ensemble of interactive trackers. Bailer et al. [29] used an optimization approach based on dynamic programming to fuse the predictions of multiple trackers without their interaction. For an analogous setting, Dunnhofer et al. [31] presented a tracker selection strategy based on a value function approximation learned offline via knowledge distillation and reinforcement learning (RL). Similarly, Song et al. [41] proposed an online selection policy optimized with hierarchical RL.

The main drawback of the solutions presented here is that they were studied for the fusion of trackers in the context of short-term tracking. In contrast, in this paper we focus on the long-term setting and, to the best of our knowledge, the proposed study is new in such a context.

III. METHODOLOGY

The key idea of this paper is to develop an effective strategy to fuse the capabilities of complementary trackers in the context of long-term visual object tracking. Particularly, our goal is to implement a solution that achieves higher tracking performance in an online fashion by exploiting the characteristics of different trackers. After the description of some preliminary concepts, in this section we will introduce the methodology to accomplish such an objective.

A. Preliminaries

We consider a video \( V = \{ F_t \in I \}_{t=0}^{T} \), as a sequence of frames \( F_t \), where \( I = \{0, \cdots, 255\}^{w \times h \times 3} \) is the space of RGB images and \( T \in \mathbb{N} \) denotes the number of frames. Let \( b_t = [x_t, y_t, w_t, h_t] \in B \subseteq \mathbb{R}^4 \) be the \( t \)-th bounding-box defining the coordinates of the top left corner, and the width and height of the rectangle containing the target. The goal of a long-term tracker is to predict the bounding-box \( b_t \) that best fits the target and a confidence score \( c_t \in [0, 1] \) that reports whether the target is visible in the frame, for all \( F_t \). We define a tracker as a function \( \tau : I \rightarrow B \times [0, 1] \) that returns the target localization and confidence score for an input frame. At the first frame \( F_0 \), the tracker is initialized with the ground-truth bounding-box \( b_0 \) which outlines the target to be tracked.

B. Tracker Combination Procedure

We refer to our proposed combination algorithm as CoCoLoT. At every \( t \), CoCoLoT receives in input the frame \( F_t \) and outputs \( b_t \) and \( c_t \).

1) Execution of The Baseline Trackers: In this work, we selected the state-of-the-art trackers STARK [22] and SuperDiMP [13], [27] enhanced with a meta-updater [26] as the baseline trackers which capabilities are fused. Such choices are motivated by the outstanding results achieved by such algorithms in the long-term setting, and because they perform tracking by different principles. Indeed, the first method is
based on a transformer-based architecture whose tracking knowledge is acquired on a large dataset of tracking examples only through offline optimization. The second tracker instead is a deep discriminative tracker which uses an online learning mechanism to adapt a pretrained network to a new target while tracking. The aspect of performing tracking by disparate principles is especially important since complementary capabilities could benefit a combination strategy. We verified the presence of such complementary characteristics in the long-term tracking behavior of the considered trackers, and an example of outcome is proposed in Figure 2. It can be noticed that STARK manifests a better ability in producing bounding-boxes tightly fitting the targets’ appearance. This behavior results in an higher Intersection-over-Union (IoU) and tells that the tracker is more spatially accurate. Such an ability however is not consistent with the confidence predictions given by the tracker which are often wrong or overconfident. On the other hand, we observe that SuperDiMP is generally less accurate in the prediction of target localization – its IoU is lower than STARK – but its confidence predictions are definitely more consistent with such a performance, ultimately demonstrating STARK – but its confidence predictions are definitely more consistent with the confidence predictions.

In the proposed CoCoLoT pipeline, such two baseline trackers \( \tau^{(1)}, \tau^{(2)} \) are run according to their original methodology on frame \( F_t \) when CoCoLoT is inputted with frame \( F_t \). By this step, they produce the respective bounding-box \( b_t^{(i)} \) and confidence score \( c_t^{(i)}, i = 1, 2 \). It is worth notice that the two trackers are one independent from the other. It is hence possible to put in parallel the executions of the two in order to increase the processing speed of the combination strategy.

2) Target Visibility Determination: Next, CoCoLoT determines whether \( \tau^{(i)} \) are correctly following the target, i.e. if it is visible in their predicted bounding-boxes. This step is achieved by exploiting the confidence \( c_t^{(i)} \) which represent specific probability estimates of the target being present in the frame. However, relying solely on \( c_t^{(i)} \) does not enable an effective tracker selection mechanism because such estimates can be erroneous due to overconfidence or training bias. We hence propose to improve such target visibility scores through a target verification module that is independent from the baseline trackers. Particularly, we employ an online learned function \( v : \mathbb{I} \times \mathbb{B} \rightarrow [0, 1] \) that returns a probability estimate \( v_t \) of the target being present in the image patch extracted from the frame \( F_t \) considering the area determined by a bounding-box \( b_t \). This operation is inspired by the target verification operation present in different long-term tracking pipelines [26], [7], [42]. Such a verification step is implemented as a binary classification based on a deep neural network learned to distinguish between patches containing the target object and patches without. The architecture and learning procedure is akin to [43]. In short, the network is first trained offline to acquire general patch separation knowledge. During tracking, the pretrained weights are adjusted online by an optimization procedure that uses new target appearances extracted based on the latest target localization information \( b_t \). A sampling procedure is performed to generate candidate target localization around \( b_t \). Of such samples, positive target patches are those image areas whose sampled location has an IoU greater than 0.7. Negative target patches are those resulting in an IoU of 0.3 or lower instead. The execution of this update operation is triggered by a meta updater instance [26].

Hence, in CoCoLoT, the verifier \( v_t^{(i)} \) takes the frame \( F_t \) and bounding-box \( b_t^{(i)} \), and returns a tracker-independent evaluation score \( v_t^{(i)} \) for each tracker. Such a value is combined with the tracker’s confidence as

\[
\hat{c}_t^{(i)} = \frac{c_t^{(i)} + v_t^{(i)}}{2}. \tag{1}
\]

\( \hat{c}_t^{(i)} \) represents a more consistent target visibility estimation. We binarize such values with a 0.5 threshold to determine the status \( \tilde{p}_t^{(i)} \in \{0, 1\} \) of target visual presence in the single frames. However, we experienced that \( \tilde{p}_t^{(i)} \) could be wrong since the estimate is mostly based on the single-frame appearance of targets. Given that target disappearances and reappearances are dynamic processes evolving over multiple frames we consider the \( \tilde{p}_t^{(i)} \) present in the last \( \hat{T} \) frames to determine the actual target presence. Particularly, we say that the target is visible inside \( b_t^{(i)} \), and set \( p_t^{(i)} = 1 \), if

\[
\sum_{j=0}^{\hat{T}-1} \tilde{p}_t^{(i)} > \lceil 0.75 \cdot \hat{T} \rceil. \tag{2}
\]

Otherwise, we set \( p_t^{(i)} = 0 \) and the target is considered not visible in the tracker’s prediction. We experimentally found \( \hat{T} = 5 \) to be a good representation of the duration of the target disappearance/appearance process. The value \( p_t^{(i)} \) is also used by CoCoLoT as confidence prediction, i.e. \( c_t = p_t^{(i)} \).

3) Target Localization Determination: The values \( p_t^{(i)} \) determine which tracker is currently following the target. Such
information is used by CoCoLoT to select which target bounding-box to output for frame \( F_t \). If \( p_t^{(1)} \) and \( p_t^{(2)} \) are equal and greater than 0 CoCoLoT selects the box produced by \( \tau_t^{(1)} \) as output \( b_t \) since it produces more accurate bounding-boxes in general. If only one of the two \( p_t^{(i)} \) values is equal to 1 then the tracker’s box corresponding to \( i \) is determined and used as CoCoLoT’s output. If both \( p_t^{(i)} \) are zero, the bounding-box result of \( \tau_t^{(1)} \) is selected because of its better re-detection capabilities.

4) Tracker Correction: The predicted \( b_t \) is an useful resource if properly aligned on the target. We hence exploit it to correct the performance of the worse tracker. At the next \( F_{t+1} \), \( \tau_t^{(1)} \) and \( \tau_t^{(2)} \) search for the target in an image area determined by the previously known bounding-box \( b_t^{(1)} \). We propose to modify \( b_t^{(1)} \) to match \( b_t \) when \( p_t^{(1)} = 1 \). This step has a correction effect on the behavior of \( \tau_t^{(i)} \). In fact, \( \tau_t^{(i)} \) will search for the target in a local image area whose position is better aligned with the target position in \( F_{t+1} \).

IV. EXPERIMENTAL SETUP

A. Datasets

We conducted experiments on the LTB-50 [5] benchmark. This dataset is used in the annual VOT challenges [7], [27], [34], and it is composed of 50 videos for a total of around 215K frames densely labeled with the bounding-boxes of diverse objects (people, car, motorcycles, bicycles, boat, animals, etc.). Each video contains circa 10 long-term target disappearances on average each lasting for circa 52 frames. Evaluations were also performed on the TLP dataset [32]. This benchmark is composed of 50 video sequences comprising around 676K labeled frames. The average length of the sequences in time is over 8 minutes. We also ran experiments on the test set of the LaSOT benchmark [33]. This is composed of 280 sequences with around 690K frames and a average sequence length of 2500 frames.

B. Evaluation Protocol and Measures

For all the experiments over all the benchmarks, we run trackers according to the standard protocol [5], [6], [7] of initializing the tracker in the first frame and then execute it on every other frame to obtain bounding-box and confidence predictions. We employed established metrics to quantify the performance of our proposed solution. For the LTB-50 benchmark, the F-score, Precision\(_{LTB} \), and Recall\(_{LTB} \) metrics [5] have been used. On the TLP dataset, we employed the Area-Under-the-Curve (AUC) of the success plot – referred to as Success\(_{TLP} \) – in which an IoU of 1 is set for all the frames where the tracker correctly predicts the absence of the target. Similarly, we also report the Precision\(_{TLP} \) which is the AUC of the precision plot in which a bounding-box distance of 0 is set for all the frames where the tracker correctly predicts the absence of the target [32]. For the LaSOT benchmark, we used the AUC of the success and the precision plots referred as Success\(_{LaSOT} \) and Precision\(_{LaSOT} \) respectively [33].

C. Improvements to STARK

We found additional improvements to the tracking strategy of the underlying trackers to benefit the performance of our overall solution CoCoLoT. In particular, we propose to control STARK’s searching area factor \( \sigma \) which defines the image area size in which to look for the target. We considered \( \sigma = \frac{7}{17} \) in all frames in which \( p_t^{(i)} = 1 \). Given that \( p_t \) establishes that CoCoLoT is following the visible target, the proposed improvement forces the tracker to better focus on it, reducing the chance of confusion due to the presence of distractors. Moreover, we found STARK to be susceptible to wrong target size estimations after the change of the dynamic template. We propose to penalize the results of STARK by setting \( c_t^{(i)} \) if the ratio between the aspect-ratio of \( b_{t-1} \) and \( b_t^{(i)} \) are not consistent with the temporal coherence of motion and scale change of a target. Overall, as we will show later, these improvements permit to avoid wrong target image patches to pollute the training data used by \( \upsilon(\cdot) \) for online adaptation, ultimately making its discriminative ability more effective.

D. Implementation Details

Code to implement the method and the experiments was implemented in Python and run on a machine with an Intel Xeon E5-2690 v4 @ 2.60GHz CPU, 320 GB of RAM and an NVIDIA TITAN V GPU. The original implementations of the STARK and SuperDiMP trackers provided by the respective authors have been used along with the pretrained models. The verifier model \( \upsilon(\cdot) \) has been implemented using the PyTorch version of the MDNet tracker [43]. CoCoLoT runs at 5 FPS on average.

V. RESULTS

In this section, we provide the results of the conducted experimental campaign. We first analyze the capabilities of CoCoLoT on the LTB-50 benchmark [5], [7] under different ablative studies and in comparison with other tracker fusion strategies. We then compare our framework with many state-of-the-art solutions on the other benchmarks described in Section IV.
Fig. 3: Qualitative examples of the tracking ability achieved by CoCoLoT in comparison with the baseline trackers STARK and SuperDiMP. The first column of images presents the first frame of each video. In the top-left corner of each frame the time elapsed since the beginning of the video is reported. Overall, our solution permits to fuse the capabilities of the underlying trackers and consequently achieve a more robust target tracking along the videos.

**TABLE II: Performance of CoCoLoT on the LTB-50 benchmark** [5], [7] in comparison with baseline strategies that combine the capabilities of the STARK and SuperDiMP trackers (whose performances are reported in the first two rows). Best result, per metric, is highlighted in bold.

| Setup            | F-Score | Precision$_{LTB}$ | Recall$_{LTB}$ |
|------------------|---------|-------------------|----------------|
| 1) SuperDiMP     | 0.671   | 0.691             | 0.692          |
| 2) STARK         | 0.696   | 0.708             | 0.685          |
| 3) $v_i^{(t)}$ and $c_i^{(t)}$ average | 0.671 | 0.723 | 0.626 |
| 4) $u_i^{(t)}$ and $c_i^{(t)}$ average and correction of both | 0.704 | 0.711 | 0.698 |
| 5) $u_i^{(t)}$ selection by maximum $c_i^{(t)}$ | 0.705 | 0.703 | 0.706 |
| 6) $u_i^{(t)}$ selection by maximum $c_i^{(t)}$ and correction of the other | 0.675 | 0.687 | 0.675 |
| 7) TRASFUST [31] | 0.701   | 0.701             | 0.684          |
| 8) CoCoLoT       | 0.735   | 0.741             | 0.729          |

**A. Ablation Study**

Table I reports the performance of CoCoLoT on the LTB-50 benchmark [5], [7] by increasingly adding the contributions described in the Section III. Improved performance with respect to the underlying trackers is already achieved by selecting the tracker obtaining the best $v_i^{(t)}$ given by the verifier (row 3). Precision$_{LTB}$ results are particularly increased by combining the trackers’ confidences and the verifier scores (row 4). Determining the target presence $p_i^{(t)}$ by the scores achieved in the previous $\hat{T}$ frames additionally increases the precision (row 6). Row 5 and 7 show the performance is additionally improved by the interaction and correction process between trackers. By this setup, the performance gain with respect to the best of the underlying trackers is of around 3.7% in F-Score, 2.8% in Precision$_{LTB}$, and 4.7% in Recall$_{LTB}$. The introduction of the improvements to STARK enables the $v(\cdot)$ to remove polluted samples during the training set used for online learning (row 7 and 8). This results in a more consistent optimization process that ultimately enables a better target-background discrimination. Notice that the same strategies activated on the underlying STARK tracker based on its confidence $c_i^{(t)}$ make it achieve an F-Score of 0.694 and 0.689 for the adapting searching area and aspect-ratio correction respectively. These outcomes suggest that such strategies have to be applied carefully only when the estimation of target presence is sufficiently accurate. Overall, the performance gain of our overall system with respect to the best of the underlying trackers is of 5.6% in F-Score, 4.7% in Precision$_{LTB}$, and 6.4% in Recall$_{LTB}$. Some qualitative examples of the performance of CoCoLoT in comparison with the baseline trackers are presented in Figure 3.

**B. Comparison with Baselines**

We compared the fusion strategy implemented by CoCoLoT with baseline and state-of-the-art tracker fusion approaches [31]. All the compared methods have been applied on top of the same STARK and SuperDiMP instances used in CoCoLoT. The results are given in Table II. CoCoLoT results much better than all the other strategies. Simply averaging the bounding-box coordinate values and respective confidence scores lowers the performance of the trackers (row 1). Correcting both trackers by their average target position and scale improves the performance of the two (row 2). Selecting the $b_i^{(t)}$ for target localization based on the maximum $c_i^{(t)}$ of each tracker allows to improve the performance again (row 3). But making the trackers interact in the latter setup results in a performance drop (row 4). We hypothesize this is due to the STARK’s overconfidence given to bounding-box predictions having low accuracy which causes the correction of the other trackers with inaccurate boxes. The fusion performance of TRASFUST [31] does not allow for performance improvement of the two underlying trackers. This happens because such a fusion strategy is designed for short-term tracking settings.

**C. Target Presence Determination**

Table III reports the performance of CoCoLoT in determining the target presence in the frames of the LTB-50 benchmark [5], [7] in comparison with the underlying trackers. Specifically, for each frame in the dataset we compared the target presence label (0 or 1) with each tracker’s presence label computed after thresholding at 0.5 the tracker’s predicted $c_i^{(t)}$. The Accuracy reports the average agreement between the ground-truth and tracker-specific labels. The Sensitivity

**TABLE III: Performance achieved by CoCoLoT in the determination of the presence of the target on the LTB-50 benchmark [5], [7] in comparison with SuperDiMP and STARK. Best result, per metric, is highlighted in bold.**

| Setup             | Accuracy | Sensitivity | Specificity |
|-------------------|----------|-------------|-------------|
| SuperDiMP         | 0.828    | 0.811       | 0.814       |
| STARK             | 0.861    | 0.860       | 0.811       |
| CoCoLoT           | **0.925**| **0.937**   | **0.782**   |

**TABLE IV: Performance achieved by CoCoLoT on the LTB-50 benchmark [5], [7] while considering different number of frames $\hat{T}$ to determine the visibility of the target. Best result, per metric, is highlighted in bold.**

| # Frames | 1 | 2 | 5 | 10 | 20 |
|----------|---|---|---|----|----|
| F-Score  | 0.728 | 0.732 | **0.735** | 0.734 | 0.719 |
| Recall$_{LTB}$ | 0.728 | 0.736 | **0.741** | 0.734 | 0.719 |
| Precision$_{LTB}$ | 0.728 | 0.728 | 0.729 | **0.731** | 0.719 |
In this paper, we focused on the problem of fusing the capabilities of complementary visual trackers in long-term scenarios. We proposed CoCoLoT, a framework in which an effective evaluation strategy based on an online learned deep learning model is used to assess the behavior of the underlying trackers STARK [22] and SuperDiMP [13], [27]. Based on the proposed evaluation function, a selection policy was implemented to select which of the two trackers provides the best target localization. Such an outcome was used to localize the target and also to correct the performance of the non-selected tracker, ultimately correcting both trackers from errors by themselves. We provided extensive experimental results to understand the impact of the modules composing our solution. Results are very interesting and competitive with the state-of-the-art on the LTb-50 [5], [7], TLP [32], and LaSOT [33] benchmarks.

**VI. CONCLUSIONS**

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