Real-time Deep Tracking via Corrective Domain Adaptation

Hanxi Li, Xinyu Wang, Fumin Shen, Yi Li, Fatih Porikli, Mingwen Wang

***Abstract*—Visual tracking is one of the fundamental problems in computer vision. Recently, some deep-learning-based tracking algorithms have been illustrating record-breaking performances. However, due to the high complexity of neural networks, most deep trackers suffer from low tracking speed, and thus are impractical in many real-world applications. Some recently-proposed deep trackers with smaller network structure achieve high efficiency while at the cost of significant decrease on precision. In this paper, we propose to transfer the deep feature which is learned originally for image classification to the visual tracking domain. The domain adaptation is achieved via some "grafted" auxiliary networks which are trained by regressing the object location in tracking frames. This adaptation improves the tracking performance significantly, both on accuracy and efficiency. The yielded deep tracker is real-time and also illustrates the state-of-the-art accuracies in the experiment involving two well-adopted benchmarks with more than 100 test videos. Furthermore, the adaptation is also naturally used for introducing the objectness concept into visual tracking. This removes a long-standing target ambiguity in visual tracking tasks and we illustrate the empirical superiority of the more well-defined task.**

***Index Terms*—Visual tracking, deep learning, real-time**

I. Introduction

Visual tracking is one of the fundamental computer vision tasks. During the last decade, as the surge of deep learning, more and more tracking algorithms benefit from deep neural networks, e.g. Convolutional Neural Networks [1], [2] and Recurrent Neural Networks [3], [4]. Despite the well-admitted success, a dilemma still existing in the community is that, deep learning increases the tracking accuracy, while at the cost of high computational complexity. As a result, most well-performing deep trackers usually suffer from low efficiency [5], [6]. Recently, some real-time deep trackers were proposed [7], [8], [9]. They achieved very fast tracking speed, but can not beat the shallow methods in some important evaluations, as we illustrate later.

First two authors contributed equally.

Manuscript received x x, xxxx; revised x x, xxxx; accepted x x, xxxx. date of current version x x, xxxx. This work was supported by the National Natural Science Foundation of China (Grant No. 61672079). This paper was recommended by Associate Editor X. x. (*Corresponding author: Fumin Shen*).

H. Li and M. Wang are with the School of Computer and Information Engineering, Jiangxi Normal University, Nanchang 330022, China (e-mail: lihanxi2001@gmail.com; mwwang@jxnu.edu.cn).

X. Wang is with Australian Institute for Machine Learning (AIML), the University of Adelaide, SA 5005, Australia. (e-mail: xinyu.wang02@adelaide.edu.au).

F. Shen is with the Center for Future Media, University of Electronic Science and Technology of China, Chengdu 611731, China. (e-mail: fumin.shen@gmail.com)

Yi. Li is with Google Brain and X, the Moonshot Factory. (e-mail: liyi.umd@gmail.com).

F. Porikli is with Research School of Engineering, Australian National University, Canberra, ACT 0200, Australia. (e-mail: fatih.porikli@anu.edu.au)

In this paper, a simple yet effective domain adaptation algorithm is proposed. The equipped tracking algorithm, termed Corrective Domain Adaptation (CODA), transfers the features from the classification domain to the tracking domain, where the individual objects, rather than the image categories, are used as the learning samples. Figure 1 illustrates the main concept of the proposed domain adaptation, in a high level. The advantage of the proposed domain adaptation is three-fold. First, the shallow visual tracker, *e.g.*, the KCF algorithm employed in this work, can extract more informative deep features from the transferred feature space. Secondly, the adaptation could be also viewed as a dimension-reduction process that removes the redundant information for tracking, and more importantly, reduces the channel number of the deep feature significantly. This leads to a remarkable increase on tracking speed. Last but not least, the adaptation introduces small auxiliary CNN "branches" that could seamlessly correct the predictions of the shallow visual trackers. Inspired by the successful adoption of objectness in visual tracking [10], [11], we exploit the category information of the tracking target in CODA, in a relatively natural way. For a certain object category, the CNN "branches" are fine-tuned to correct the tracking boxes, and thus higher tracking accuracies are obtained.

The experiments show that the proposed CODA algorithm runs in around 35 FPS while achieves comparable tracking accuracy to the state-of-the-art trackers. To our best knowledge, our CODA is the best-performing real-time visual tracker. Furthermore, given the category information of the tracking target, the corrective CNN branches lead to a significant boost in tracking accuracy while keep the tracking speed nearly unchanged. In summary, the main contribution of this paper includes:

- We propose a simple yet effective domain adaptation method for visual tracking. The adaptation not only leads to a real-time tracking speed, but also remains a high tracking accuracy which is comparable to the state-of-the-art trackers.
- For a certain type of tracking target, we propose to use the CNN branches, which are originally trained to adapt the deep feature to the visual tracking domain, to correct the initial tracking boxes. Within a sophisticated inference framework, the tracking accuracy boosts dramatically.
- From another perspective, the success of the corrective adaptation empirically proofs that a more well-defined tracking target, rather than a simple bounding-box, could benefit the tracking process significantly. In other words, this work offers an alternative to addressing the long-standing "ill-posed" problem in visual tracking.

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TCSVT.2019.2923639, IEEE Transactions on Circuits and Systems for Video Technology

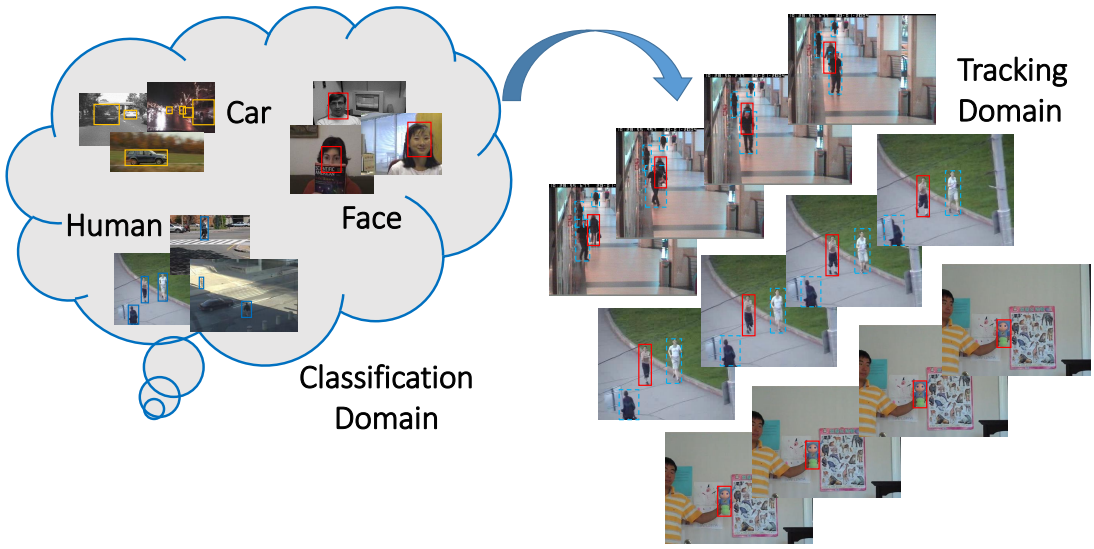


Fig. 1. The high level concept of the proposed CODA tracker. Left: most of the deep neural network is pretrained for image classification, where the learning algorithm focus on object classes. Right: an adaptation is performed to transfer the classification features to the visual tracking domain, where the learning algorithm treats the individual object independently.

II. Related work

A. Deep trackers

Similar to other fields of computer vision, in recent years, more and more state-of-the-art visual trackers are deep-learning based. [1] is a well-known pioneering work that learns deep features for visual tracking. The DeepTrack method [10], [2] learns a deep model from scratch at the first frame and then updates it online. [12], [13] adopt the similar learning strategy, *i.e.*, learning the deep model offline with a large number of images while updating it online for the current video sequence. [14] achieves real-time speed via replacing the slow model update with a fast inference process.

The HCF tracker [5] extracts hierarchical convolutional features from the VGG-19 network [15], then put the features into correlation filters to regress the respond map. It can be considered as a combination between deep learning and the fast shallow tracker based on correlation filters. It achieves high tracking accuracy while the speed is around 10 fps.

Hyeonseob Nam *et al.* proposed to pre-train deep CNNs in multi domains, with each domain corresponding to one training video sequence [6]. The authors claim that there exist some common properties that are desirable for target representations in all domains such as illumination changes. To extract these common features, the authors separate domain-independent information from domain-specific layers. The yielded tracker, termed MD-net, achieves excellent tracking performance while the tracking speed is only 1 fps.

B. Real-time deep trackers

Recently, some real-time deep trackers have also been proposed. [14] propose to infer the target location based on the deep features extracted from a fixed CNN model. Without updating the CNN model, it achieves real-time speed. In [7], David Held *et al.* learn a deep regressor that can predict the location of the current object based on its appearance in the last frame. The tracker obtains a much faster tracking speed (over 100 fps) comparing to conventional deep trackers. Similarly, in [8] a fully-convolutional siamese network is learned to match the object template in the current frame. It also achieves real-time speed. Even though these real-time deep trackers also illustrate high tracking accuracy, there is still a clear performance gap between them and the state-of-the-art deep trackers. [16] discusses how different regularization terms of correlation filters essentially influence the tracking performance. The yielded variations of KCF tracker achieve higher tracking accuracy than the ordinary KCF, at the cost of speed reduction (from the speed over 100 fps of the original KCF to around 37 fps).

C. Deep tracking with objectness

Nearly all the deep trackers exploit the information of generic or specific object categories to achieve higher tracking accuracies. Most of the state-of-the-art deep trackers involve the objectness implicitly via pre-training the network off-line on the dataset with object categories and bounding-boxes. [1], [14], [13], [6], [17]. [11] designs a heuristic object proposal algorithm for eliminating the non-object tracking candidates and thus the tracker can hardly lose the target due to a mis-leading background patch. While most of the methods mainly focus on the generic objectness, [10] pay more attention to the specific object categories. By pre-training the CNN model with the object samples from a certain category, *e.g.*, human faces, the DeepTrack algorithm performs more robust for the specific object type.

[10] and [11] has illustrated the superiority of a more well-defined tracking task based on the introduction of objectness. In fact, the introduction partially addresses the "ill-posed"

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TCSVT.2019.2923639, IEEE Transactions on Circuits and Systems for Video Technology

problem in visual tracking which causes a long-standing criticism to tracking tasks. Following the high-level methodology of the pioneering work, we propose to leverage the information of tracking target category in our CODA algorithm, as we illustrate in Section IV-B.

D. Deep detectors

Similar to the visual tracking area, object detection algorithms have also been enjoying the "deep learning revolution" for a couple of years. The early successful deep detectors [18], [19] demonstrate high accuracy while the detection speed is low. Some faster deep detectors are then designed and proposed [20], [21], [22] and the most recently proposed approaches [23], [24] achieve both high detection efficiency and accuracy.

By noticing that most of the state-of-the-art visual trackers employ the "tracking-by-detection" strategy where the visual tracker is essentially a target detector. The deep detector and deep tracker are very similar from the methodology perspective. Moreover, even though there are various deep trackers and detectors, they use very limited types of neural networks, such as VGG-16/19 [15] or the residual network [25]. Those connections imply a better visual tracking algorithm can be obtained if the tracker is fused with a deep detector properly. In this paper, we enhance the deep tracking algorithm using the learning and inference strategies of a sophisticated deep detector, as we show in Section III.

III. Domain adaptation for robust and real-time visual tracking

In this section, we introduce the details of the proposed tracking algorithm, *i.e.*, the Corrective Domain Adaptation (CODA) tracker.

A. Network structure

The proposed work is developed based on the HCF [5] tracking algorithm which is one of the state-of-the-art visual trackers. In HCF, deep features are firstly extracted from multiple layers of the VGG-19 network [15], and a set of KCF [26] trackers are carried out on those features, respectively. The final tracking prediction is obtained in a weighted voting manner. Following the setting in [5], we also extract the deep features from $conv3\_5$, $conv4\_5$ and $conv5\_5$ network layers of the VGG-19 model. However, the VGG-19 network is pre-trained using the ILSVRC dataset [27] for image classification, where the learning algorithm usually focus on the object categories. This is different from visual tracking tasks, where the individual objects are distinguished from other ones (even those from the same category) and the background. Intuitively, it is better to transfer the classification features into the visual tracking domain.

In this work, we propose to perform the domain adaptation in a simple way. A "tracking branch" is "grafted" onto each feature layer, as shown in Fig. 8. The tracking branch is actually a convolution layer which reduces the channel number by 8 times and keeps feature map size unchanged. The convolution layer is then learned via minimizing the loss function tailored for tracking, as introduced below.

B. Learn the domain adaptation

The parameters in the aforementioned tracking branch is learned following a similar manner as Single Shot MultiBox Detector (SSD), a state-of-the-art detection algorithm [22]. When training, the original layers of VGG-19 (*i.e.* those ones before $conv\_5$ are fixed and each "tracking branch" is trained independently) The flowchart of the learning procedure for one tracking branch (based on $conv3\_4$) is illustrated in upper row of Figure 3, comparing with the learning strategy of MD-net [6] (the bottom row). To obtain a completed training circle, the adapted feature in $conv3\_5$ is used to regress the objects' locations and their objectness scores (shown in the dashed block). Please note that the deep learning stage in this work is purely offline and the additional part in the dashed block will be abandoned for generic object tracking. For specific categories, we propose to utilize the "tracking branches" for correcting the initial tracking boxes.

In SSD, a number of "default boxes" are generated for regressing the object rectangles. Furthermore, to accommodate the objects in different scales and shapes, the default boxes also vary in size and aspect ratios. Let $m_{i,j} \in \{1, 0\}$ be an indicator for matching the i-th default box to the j-th ground truth box. The loss function of SSD writes:

$$L(m, c, l, g) = \frac{1}{N}\left(L_{conf}(m, c) + \alpha L_{loc}(m, l, g)\right) \quad (1)$$

where c is the category of the default box, l is the predicted bounding-box while g is the ground-truth of the object box, if applicable. For the j-th default box and the i-th ground-truth, the location loss $L_{loc}^{i,j}$ is calculated as

$$L_{loc}^{i,j}(l, g) = \sum_{u \in \{x,y,w,h\}} m_{i,j} \cdot \text{smooth}_{L_1}(l_i^u - \hat{g}_j^u) \quad (2)$$

where $\hat{g}^u, u \in \{x, y, w, h\}$ is one of the geometry parameter of normalized ground-truth box.

However, the task of visual tracking differs from detection significantly. We thus tailor the loss function for the KCF algorithm, where both the object size and the KCF window size are fixed. Recall that, the KCF window plays a similar role as default boxes in SSD [26], we then only need to generate one type of default boxes and the location loss $L_{loc}^{i,j}(l, g)$ is simplified as

$$L_{loc}^{i,j}(l, g) = \sum_{u \in \{x,y\}} m_{i,j} \cdot \text{smooth}_{L_1}(l_i^u - g_j^u) \quad (3)$$

In other words, only the displacement $\{x, y\}$ is taken into consideration and there is no need for ground-truth box normalization.

Note that the concept of domain adaptation in this work is different from that defined in MD-net [6], where different video sequences are treated as different domains and thus multiple fully-connected layers are learned to handle them (see Figure 3). This is mainly because in MD-net samples the training instances in a sliding-window manner. An object labeled negative in one domain could be selected as a positive sample in another domain. Given the training video number is C and the dimension of the last convolution layer is d_c,

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TCSVT.2019.2923639, IEEE Transactions on Circuits and Systems for Video Technology

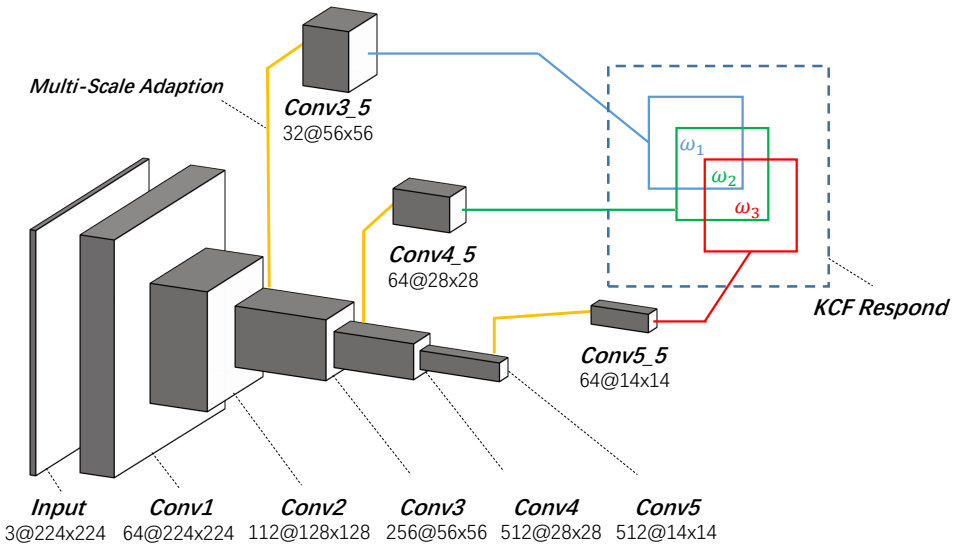


Fig. 2. The network structure of the proposed CODA tracker. Three layers, namely, $conv3\_5$, $conv4\_5$ and $conv5\_5$ are selected as feature source. The domain adaption (as shown in yellow lines) reduces the channel number by 8 times and keeps feature map size unchanged. Better viewed in color.

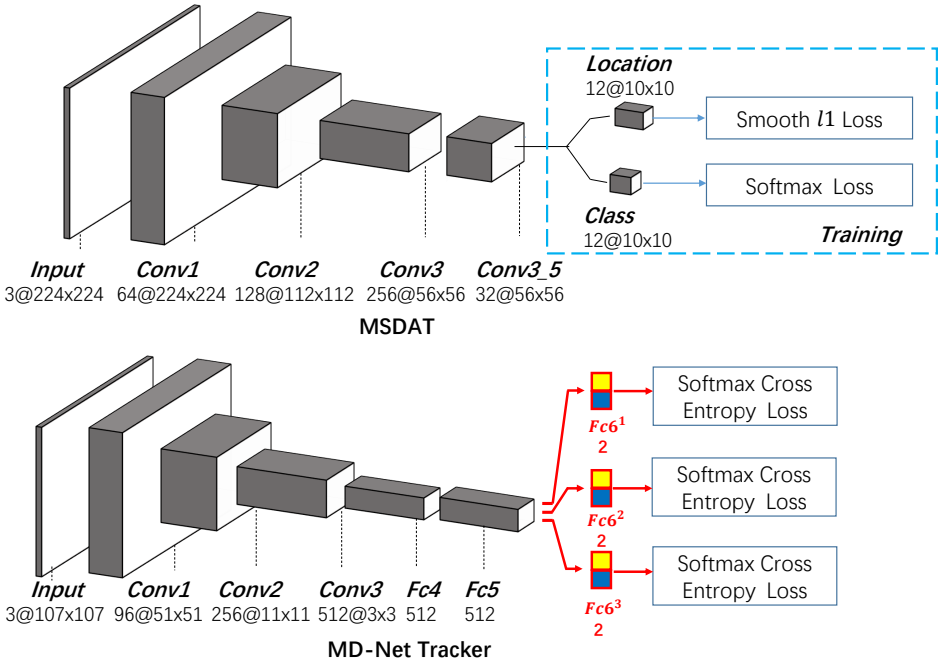


Fig. 3. The flow-charts of the training process of CODA and MD-net. Note that the network parts inside the dashed blocks are only used for training and will be abandoned before tracking. Better viewed in color.

the MD-net learns C independent $d_c \times 2$ fully-connected alternatively using C soft-max losses, *i.e.*,

$$\mathcal{M}_{fc}^i : \mathbb{R}^{d_c} \rightarrow \mathbb{R}^2, \forall i = 1, 2, \ldots, C \tag{4}$$

where $\mathcal{M}_{fc}^i, \forall i \in \{1, 2, \ldots, C\}$ denotes the C fully-connected layers that transferring the common visual domain to the individual object domain, as shown in Figure 3.

Differing from the MD-net, the domain in this work refers to a general visual tracking domain, or more specifically, the KCF domain. It is designed to mimic the KCF input in visual tracking (see Figure 3). In this domain, different tracking targets are treated as one category, *i.e.*, objects. When training, the object's location and confidence (with respect to the objectness) are regressed to minimize the smoothed l_1 loss. Mathematically, we learn a single mapping function $\mathcal{M}_{conv}(\cdot)$ as

$$\mathcal{M}_{conv} : \mathbb{R}^{d_c} \rightarrow \mathbb{R}^4 \tag{5}$$

where the $\mathbb{R}^4$ space is composed of one $\mathbb{R}^2$ space for displacement $\{x, y\}$ and one label space $\mathbb{R}^2$.

Compared with Equation 4, the training complexity in Equation 5 decreases and the corresponding convergence becomes more stable. Our experiment proves the validity of the proposed domain adaptation approach.

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TCSVT.2019.2923639, IEEE Transactions on Circuits and Systems for Video Technology

C. Multi-scale domain adaptation

As introduced above, the domain adaption in our CODA method is essentially a convolution layer. To design the layer, an immediate question is how to select a proper size for the filters. According to Figure 8, the feature maps from different layers vary in size significantly. It is hard to find a optimal filer size for all the feature layers. Inspired by the success of Inception network [28], we propose to simultaneously learn the adaptation filters in different scales. The response maps with different filter sizes are then concatenated accordingly, as shown in Figure 4. In this way, the input of the KCF tracker involves the deep features from different scales.

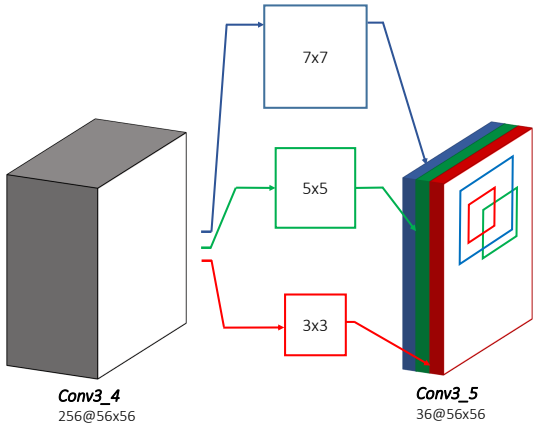


Fig. 4. Learn the adaptation layer using three different types of filters

In practice, we use 3×3 and 5×5 filters for all the three feature layers. Given the original channel number is K, each type of filter generate $\frac{K}{16}$ channels and thus the channel reduction ratio is still $8:1$.

D. Make the tracker real-time

1) Channel reduction

One important advantage of the proposed domain adaptation is the improvement of the tracking speed. It is easy to see that the speed of KCF tracker drops dramatically as the channel number increase. In this work, after the adaptation, the channel number is shrunk by 8 times which accelerates the tracker by 2 to 2.5 times.

2) Lazy feed-forward

Another effective way to increase the tracking speed is to reduce the number of feed-forwards of the VGG-19 network. In HCF, the feed-forward process is conduct for two times at each frame, one for prediction and one for model update [5]. However, we notice that the displacement of the moving object is usually small between two frames. Consequently, if we make the input window slightly larger than the KCF window, one can reuse the feature maps in the updating stage if the new KCF window (defined by the predicted location of the object) still resides inside the input window. We thus propose a lazy feed-forward strategy, which is depicted in Figure 5.

In this work, we generate the KCF window using the same rules as HCF tracker [5], the input window is 10% larger than the KCF window, both in terms of width and height. Facilitated by the lazy feed-forward strategy, in the proposed algorithm, feed-forward is conducted only once in more than 60% video frames. This gives us another 50% speed gain.

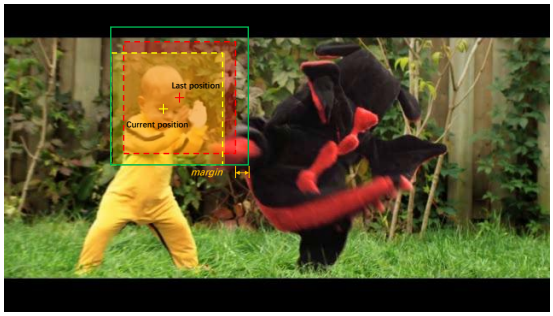


Fig. 5. The illustration of lazy feed-forward strategy. To predict the location of the object (the boy's head), a part of the image (green window) is cropped for generating the network input. Note that the green window is slightly larger than the red block, *i.e.*, the KCF window for predicting the current location. If the predicted location (shown in yellow) still resides inside the green lines, one can reuse the deep features by cropping the corresponding feature maps accordingly.

IV. Corrective Domain Adaptation for Specific Object Categories

A. A long-standing ambiguity in visual tracking

Despite the widespread real-world usages, visual tracking is still criticized as less well-posed compared with other tasks with clearly-defined targets, such as object detection and semantic segmentation. In visual tracking, the only reliable target information is given at the first frame while the information could be ambiguous or misleading in many circumstances. For example, in Figure 6, a car is to be tracked in the sequence. From the viewing angle at the first frame, only the car back can be observed so it is defined as the "target" by the blue bounding box. Nonetheless, this simple target definition usually leads to an ambiguity: when the target pose changes significantly, it is hard to evaluate tracking results. In specific, as shown in Figure 6, either the yellow box or the blue box can be considered as a "perfect" tracking, depending on what exactly the tracking target is, the car back or the whole car.

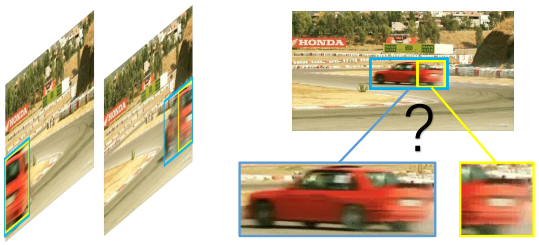


Fig. 6. The commonly existing ambiguity in visual tracking. From left to right, the car back is labeled as the tracking target at the first frame, as the viewing angle changes, the car back and the visible part of the car become more and more different. Finally, when the pose changes significantly, as shown in the right column, it is hard to judge which bounding box (among blue and yellow ones) is the better tracking result.

Unfortunately, a clearly-defined tracking target is usually absent in visual tracking due to the very limited information,

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TCSVT.2019.2923639, IEEE Transactions on Circuits and Systems for Video Technology

namely, a bounding box, given at the first frame. In this work, we try to address the ill-posed problem via imposing the object category in visual tracking tasks. In other words, the tracker tracks the object given the target's bounding box at the first frame as well as the category of the target. This assumption is similar to the original DeepTrack algorithm [10] while we exploit the object information in a easier yet more effective way.

B. Corrective Domain Adaptation

Given the specific target category, we naturally use the proposed learning strategy proposed in Section III-B to learn a set of CNN "branches" on the samples from this category and then use the "branches" for correcting the prediction of the deep tracker. The high-level concept of the "tracking-detection-fusion" is illustrated in Figure 2

From Figure 2 one can see that the CNN model is essentially the same to that in Figure 8 expect that the auxiliary CNN branches are used for regressing the object bounding box. Note that all the regression branches are not computationally complex compared with the whole network, the extra computation burden is not heavy.

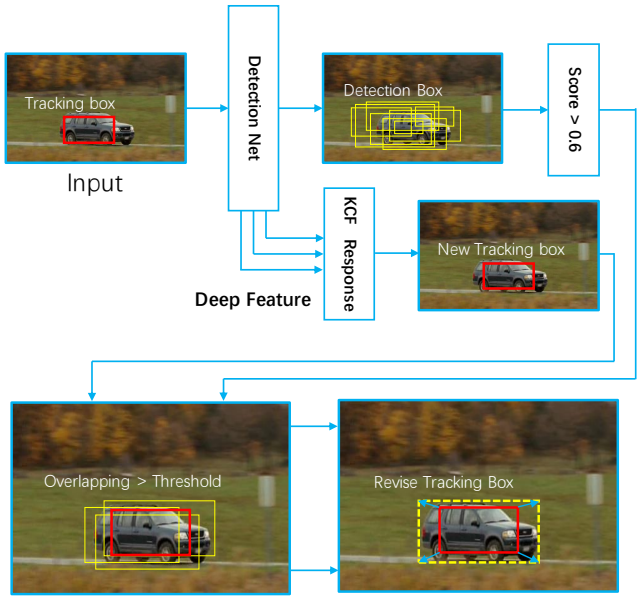


Fig. 7. The flowchart of the detection-guided tracking process. Top: the tracking box (shown in red) is obtained following the same strategy as HCF. Meanwhile, some detection bounding boxes are also generated by SSD. Bottom: after removing the unqualified detection bounding boxes, the average scale and aspect ratio of the detections are used to correct the current tracking box. Better view in color.

C. A simple yet effective guidance from detector

Given the tracking bounding-box and detection bounding-boxes, CODA merges the results in a simple yet effective way. Figure 7 demonstrates the merging process. Specifically, let us assume the tracking bounding-box (red bounding-box obtained in the same way as the ordinary HCF tracker) is represented as a 4-D vector $\mathbf{B}_t = [x_t, y_t, w_t, h_t] \in \mathbb{R}^{4\times 1}$ where x_t, y_t, w_t and h_t are the x-axis coordinate of the box center, the y-axis coordinate of the box center, the width and the height of the tracking box, respectively. The SSD detector generates multiple detection bonding-boxes stored in the set $\mathbb{B}_d = \{\mathbf{B}_d^1, \mathbf{B}_d^2, \dots \mathbf{B}_d^N\}$ with the SSD scores $\{s_d^1, s_d^2, \dots, s_d^N\}$. As shown in Figure 7, we firstly remove some unqualified detection boxes that are far away from the tracking box or with low scores. Normally, the qualified detection box set is selected as

$$\mathbb{B}'_d = \{\forall \mathbf{B}_d^i \mid \mathrm{IoU}(\mathbf{B}_d^i, \mathbf{B}_t) > 0.5 \ \& \ s_d^i > 0.6\} \tag{6}$$

where the function $\mathrm{IoU}(\mathbf{B}_1, \mathbf{B}_2)$ stands for the "Intersection over Union" of two bounding boxes $\mathbf{B}_1$ and $\mathbf{B}_2$, which is used for evaluate their overlapping state.

We use $a_t = \sqrt{w_t \cdot h_t}$ and $r_t = w_t/h_t$ to represent the scale and aspect ratio of the tracking box. Suppose the number of qualified detection boxes is N_q, we calculate the average scale and aspect ratio for the qualified detection boxes as

$$\bar{a}_d = \frac{1}{N_q} \sum_{\mathbf{B}_d^i \in \mathbb{B}'_d} a_d^i \tag{7}$$

$$\bar{r}_d = \frac{1}{N_q} \sum_{\mathbf{B}_d^i \in \mathbb{B}'_d} r_d^i \tag{8}$$

Then the scale and aspect ratio of the final prediction, *i.e.*, a_t^* and r_t^* are given by

$$a_t^* = \left(1 - \frac{1}{1+\exp(-\lambda(s_d^* - s_0))}\right) \cdot a_t + \frac{1}{1+\exp(-\lambda(s_d^* - s_0))} \cdot \bar{a}_d \tag{9}$$

$$r_t^* = \left(1 - \frac{1}{1+\exp(-\lambda(s_d^* - s_0))}\right) \cdot r_t + \frac{1}{1+\exp(-\lambda(s_d^* - s_0))} \cdot \bar{r}_d \tag{10}$$

where $s_d^* = \max([s_d^1, s_d^2, \dots, s_d^{N_q}])$, *i.e.*, the max scores over the qualified detection boxes. The hyper-parameters λ and s_0 are set to 10 and 0.6 in practice.

Finally, the predicted bounding-box of CODA writes

$$\mathbf{B}_t^* = \left[x_t, y_t, \frac{w_t \cdot a_t^*}{a_t}, \frac{w_t \cdot a_t^*}{a_t \cdot r_t^*}\right]. \tag{11}$$

From Equation 11 and Figure 7 one can see the original HCF tracking box is corrected by the detection boxes. We found the correction is usually beneficial thanks to the more clear definition of the target category and the well-learned detector. To make the corrective adaptation more clear for readers, we summarize the whole process in Algorithm 1.

V. Experiment

A. Experiment overview

In this section, we evaluate the proposed CODA tracker in two scenarios. First, the CODA for generic objects in which the corrective CNN branches are abandoned. And second, the CODA for specific target categories. The experiment is conducted on several well-adopted datasets and compared with some state-of-the-art trackers, especially the recently proposed real-time deep trackers.

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TCSVT.2019.2923639, IEEE Transactions on Circuits and Systems for Video Technology

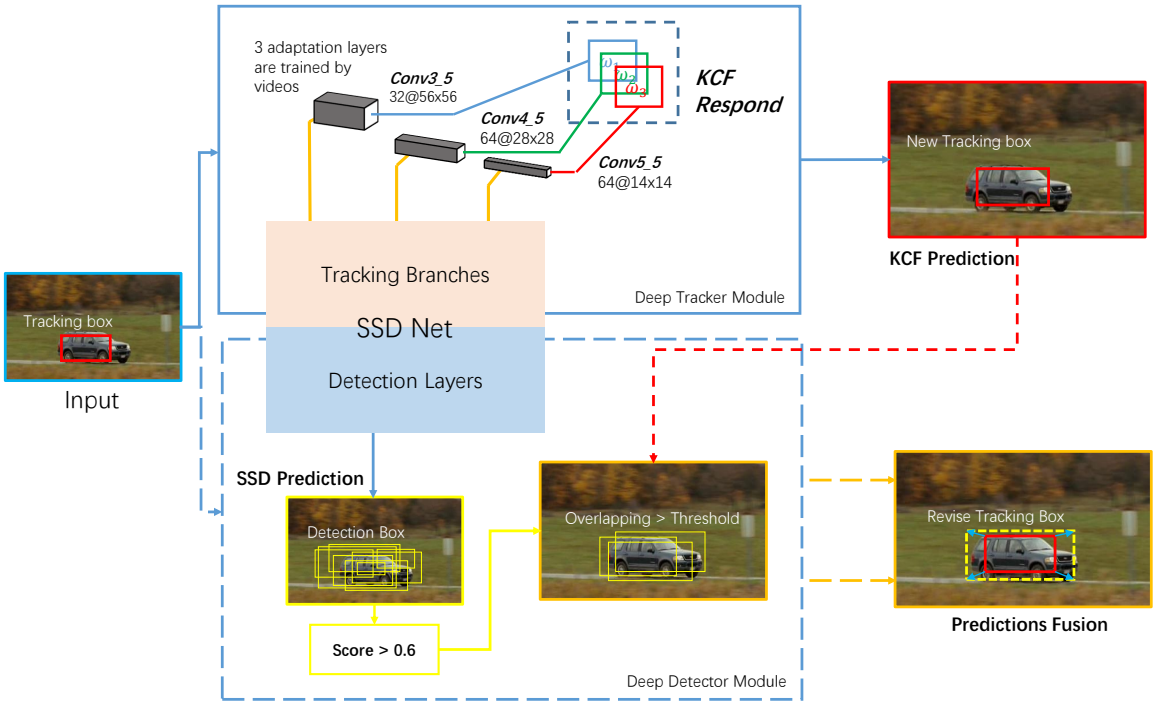


Fig. 8. For a specific target object. CODA extracts features from $conv3\_3$, $conv4\_3$ and $conv5\_3$ for KCF tracking and extracts features from other 6 layers for SSD regressing the object bounding-box. The predictions of the KCFs and the detection regressors are then merged for more robust tracking results.

The proposed CODA tracker is based on a VGG-19 network [15] which is initialized using the ILSVRC classification dataset, and then trained 3 domain adaptation layers which transfer the deep features from classification domain to tracking domain. All the experiment is implemented in MATLAB with matcaffe [29] deep learning interface, on a computer equipped with a Intel i7 4770K CPU, a NVIDIA GTX1070 graphic card and 32G RAM.

B. Experiment on generic objects

In this subsection, we report the tracking performances on generic objects of the proposed tracker and some state-of-the-art approaches. As this work focus on real-time or semi-real-time trackers, we compare our algorithm with HCF [5], GOTURN [7] which are two recently proposed fast trackers. Some well-performing shallow visual trackers, such as the KCF tracker [26], TGPR [30], Struck [31], MIL [32], TLD [33] and SCM [34] are also involved as baselines. Furthermore, two state-of-the-art deep trackers, *i.e.*, MD-net [6] and the Siamese tracker [8] are also compared. As explained above, for generic objects, the corrective CNN branches are abandoned and only the KCF tracking results are used.

1) Results on OTB-50

Similar to its prototype [35], the Object Tracking Benchmark 50 (OTB-50) [36] consists 50 video sequences and involves 51 tracking tasks. It is one of the most popular tracking benchmarks since the year 2013, The evaluation is based on two metrics: center location error and bounding box overlap ratio. The one-pass evaluation (OPE) is employed to compare our algorithm with the HCF [5], GOTURN [7], the Siamese tracker [8] and the afore mentioned shallow trackers.

The 3 domain adaptation layers of CODA are trained on 58 video sequences that collected from VOT2013 [37], VOT2014 [38] and VOT2015 [39], excluding the ones also include in OTB50. The result curves are shown in Figure 9.

From Figure 9 we can see, the proposed CODA method beats all the competitor in the overlapping evaluation while ranks second in the location error test, with a trivial inferiority (88.01 v.s. 89.07) to its prototype, the HCF tracker. Recall that the CODA beats the HCF with a similar superiority (61.41 v.s. 60.47) and runs 3 times faster than HCF, one can consider the CODA as a major variation of the HCF, with much higher speed and maintains its accuracy. From the perspective of real-time tracking, our method performs the best in both two evaluations. To our best knowledge, the proposed CODA method is the best-performing real-time tracker in this well-accepted test.

2) Results on OTB-100

The Object Tracking Benchmark 100 is the extension of OTB-50 and contains 100 video sequences. We test our method under the same experiment protocol as OTB-50 and comparing with all the aforementioned trackers. The training set of the CODA learning keeps the same to the experiment on OTB-50. The test results as well as the tracking speeds (in fps) are reported in Table I

As can be seen in the table, the proposed CODA algorithm keeps its superiority over all the other real-time trackers and keeps the similar accuracy to HCF. The best-performing MD-net (according to our best knowledge) enjoys a remarkable

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TCSVT.2019.2923639, IEEE Transactions on Circuits and Systems for Video Technology

TABLE I
TRACKING ACCURACIES AND SPEEDS (IN FPS) OF THE COMPARED TRACKERS ON OTB-100

Sequence	Ours	HCF	MD-Net	SiamFC	GOTURN	KCF	Struck	MIL	SCM	TLD
DP rate(%)	83.0	83.7	90.9	75.2	56.39	69.2	63.5	43.9	57.2	59.2
OS(AUC)	0.567	0.562	0.678	0.561	0.424	0.475	0.459	0.331	0.445	0.424
Speed(FPS)	34.8	11.0	1	58	165	243	9.84	28.0	0.37	23.3

Algorithm 1 Corrective Domain Adaptation Tracker (CODA) Algorithm

Input: Pre-trained CNN network N, video sequence S, init bbox p

$p_i = p$
$ovp = \varnothing$
for each $i \in [1, f]$ **do**
  $I_i = next(S)$; ▷ Get current frame
  if $i < I_{warm}$ **or** $sum(ovp) > t$ **then**
    $feat_i, boxes_i, scores_i = forward(I_i, N)$ ▷ Feed-forward
    $boxes_i = filtering(boxes_i, scores_i, \theta)$ ▷ Filter boxes
  else
    $feat_i = forward(I_i, N^{'})$ ▷ Forward without fully connected layer
  end if
  if i = 1 **then**
    $M_{kcf} = init(feat_i)$ ▷ Init KCF model
  else
    $p_i = predict(M_{kcf}, feat_i)$ ▷ Get predicted box
    if $boxes_i$ **then**
      $ovp_i = overlapping(boxes_i, p_i)$
      if $ovp_i > threshold$ **then**
        $p_i = merging(p_i, boxes_i)$ ▷ Predictions Fusion
      end if
    end if
  end if
  if $i > 1$ **and** $|p_i - p_{i-1}| > \tau$ **then** ▷ Lazy update strategy
    $M_{kcf} = update(M_{kcf}, feat_i)$
  end if
end for each

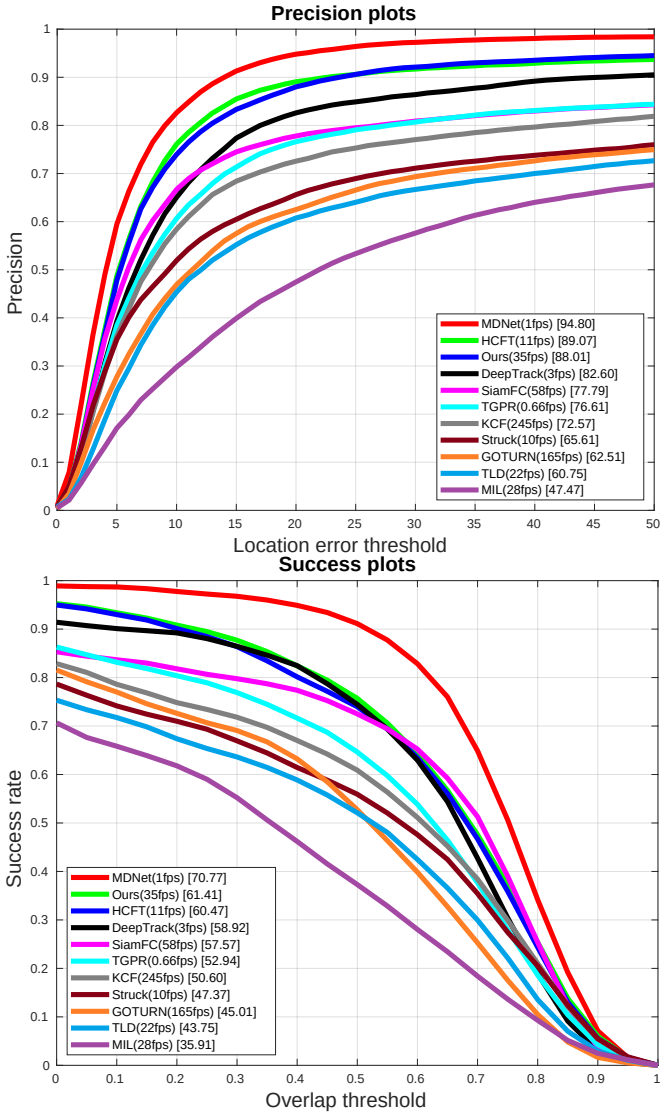


Fig. 9. The location error plots and the overlapping accuracy plots of the involving trackers, tested on the OTB-50 dataset.

performance gap over all the other trackers while runs in around 1 fps. To further illustrate the comparison between the CODA tracker and other real-time trackers, Figure 14 shows the tracking results of the comparing real-time trackers on some key frames of 9 representative OTB-100 video sequences. As a reference, the HCF results are also depicted.

3) The validity of the domain adaptation

To better verify the proposed domain adaptation, here we run another variation of the HCF tracker. For each feature layer ($conv3\_4$, $conv4\_4$ and $conv5\_4$) of VGG-19, one randomly selects one eighth of the channels from this layer. In this way, the input channel numbers to KCF are identical to the proposed CODA and thus the algorithm complexity of the "random HCF" and our method are nearly the same. The comparison of CODA, HCF and random HCF on OTB-50 is shown in Figure 10.

From the curves one can see a large gap between the randomized HCF (72.54 in location error and 50.68 in overlapping ratio) and the other two methods. In other words, the proposed domain adaptation not only reduce the channel number, but also extract the useful features for the tracking task.

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TCSVT.2019.2923639, IEEE Transactions on Circuits and Systems for Video Technology

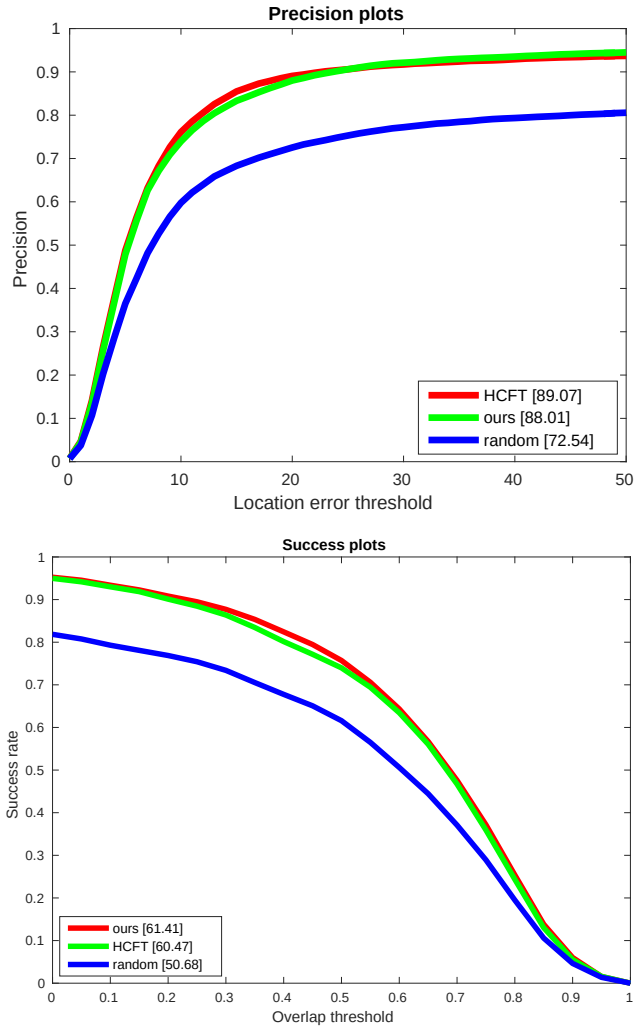


Fig. 10. The location error plots and the overlapping accuracy plots of the involving trackers, tested on the OTB-50 dataset.

C. Experiment on specific object categories

In this subsection, we test the proposed CODA tracker for specific object categories. Note that CODA can only track the object that the detector recognizes as well. The ordinary SSD is learned for predicting 20-class objects in the VOC dataset [40]. In visual tracking datasets, on the other hand, the most common categories include cars, pedestrians and human faces [36], [27]. The definition of the car category among the VOC dataset and the involved visual tracking datasets is identical. As a result, the CODA strategy can be smoothly applied on this category. In specific, we firstly pre-train the SSD-VGG-19 network for car detection on VOC2017 and VOC2012 datasets [41] and keep the detection regressors. Then the domain adaptation of CODA is then learned based on the car-subset of the original training set which is introduced in Section V-B. However, the same method can not be employed straightforwardly for pedestrians as the "person" category in VOC is defined very differently from the concept "pedestrian" in visual tracking[1]. We thus pre-train the SSD model on the the INRIA person dataset [42], which is a dedicated pedestrian detection dataset. Similar to the experiment on the car category, we keep the detection regressors for pedestrians and use the pedestrian-subset of the training set for domain adaptation. Finally, there is no face category in the VOC dataset and the definition of the "face" category is ambiguous among tracking tasks[2] and face detection tasks [43]. Obviously, a face trackers can not be guided well by a face detector with a very different definition of "face". Therefore, we do not conduct the experiment on the face category in this paper[3]. In spite of the absent face category, we still claim the experiment on cars (rigid objects) and pedestrians (non-rigid objects) is sufficient for evaluating the importance of target category information in visual tracking.

1) Results on OTB-100-Car

To evaluate the proposed method, we select all the video sequences targeting on cars from OTB-100, the totally 12 video sequences contain almost all of the tracking challenges such as scale variation, illumination variation, occlusion and motion blur. The one-pass evaluation (OPE) is employed to compare our algorithm with the HCF [5], GOTURN [7], the Siamese tracker [8] and the afore mentioned shallow trackers. The result curves are shown in Figure 11

According to Figure 11 we can see that the proposed CODA method ranks the first on location accuracy while ranks the second with the overlapping metric. It achieves significantly better results than its prototype, *i.e.*, the HCF tracker. The performance of CODA is also very close to the best-performing MD-net. Siamese tracker is also comparable to CODA and MD-net while GOTURN performs worse than the other deep trackers. On the other hand, the shallow methods perform consistently worse than the CODA, MD-Net and the Siamese tracker.

2) Results on ILSVRC2016-VID-Car

The ILSVRC(Large Scale Visual Recognition Challenge) [27] is one of the largest visual recognition datasets. The object detection from video is a new detection task in recent years, and there are 30 basic-level categories for this task, which is a subset of the 200 basic-level categories of the object detection task. We selected 58 videos that contains car from this dataset and compare the location accuracy and overlap score over the selected deep trackers [4]. As Siamese tracker and the GOTURN algorithm learned their models in this dataset, we remove them from comparison. The success plots and the precision plots are shown in Figure 12

From the figure we can see that CODA still achieves comparable accuracies as the best-performing MD-Net algorithm. The remarkable gap between the CODA's plots and the HCF's

[1]The former one includes any part of a person while the latter one usually stands for the whole human body

[2]For example, in OTB-100, some videos only annotated the facial part as "face" while others involve hair and ears

[3]A CODA-based face tracker can also be built based on a well-learned face detector while this is out of the scope of this paper

[4]We do not involve shallow trackers in this experiment as they usually perform worse than the deep ones and the results of the shallow trackers are not directly available

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TCSVT.2019.2923639, IEEE Transactions on Circuits and Systems for Video Technology

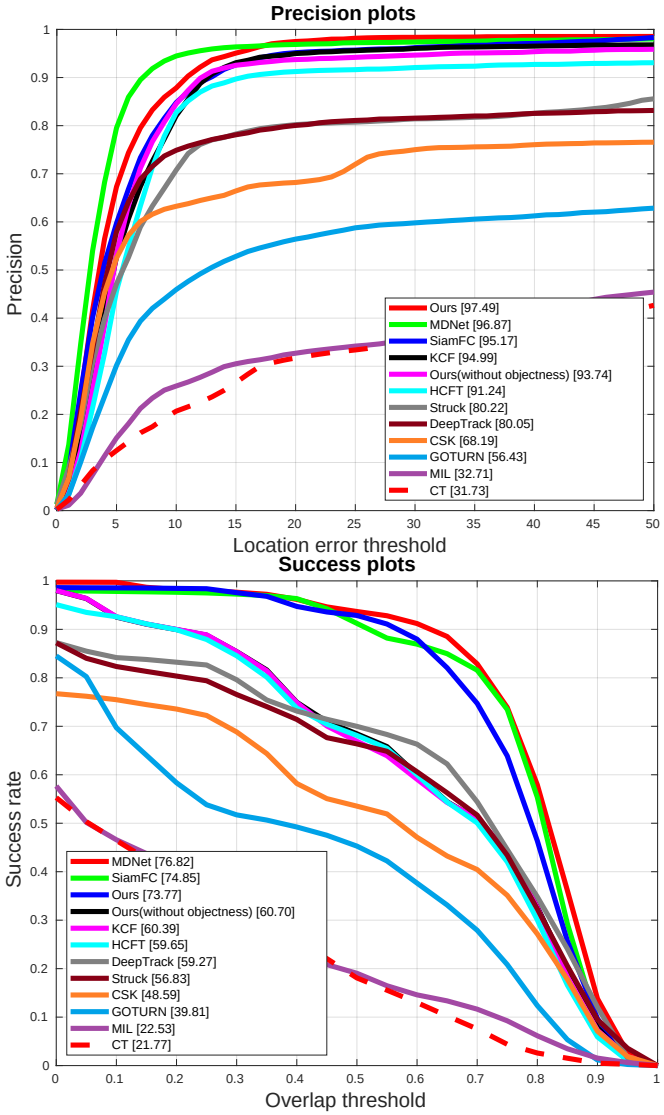


Fig. 11. The location error plots and the overlapping accuracy plots tested on the "car subset" of OTB-100. The comparing methods including MD-net [6], HCF [5], the Siamese Tracker [8], GOTURN [7], CODA (this paper) and the shallow trackers.

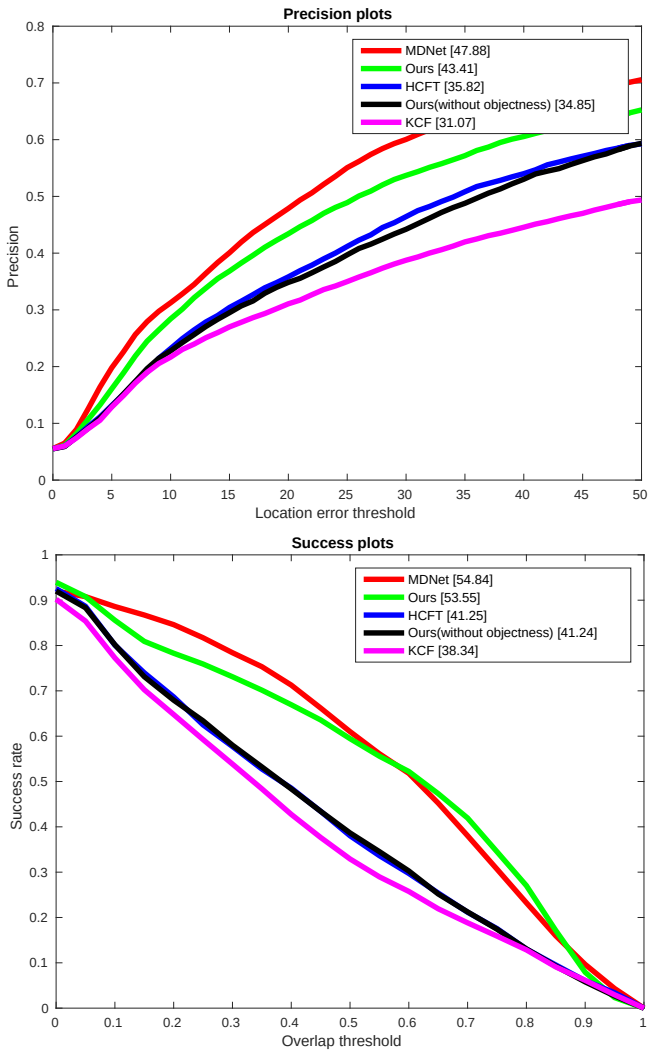


Fig. 12. The location error plots and the overlapping accuracy plots tested on the "car subset" of the ILSVRC2016-VID dataset. The comparing methods including HCF [5], our CODA tracker, MD-Net [6] and the shallow ones. We do not involve the Siamese Tracker [8] and GOTURN [7] as they are trained on this dataset.

plots proofs the validity of the introduction of the object categories.

3) Results on OTB-100-Pedestrian

We perform the same experiment on the pedestrian category to evaluate the proposed corrective framework with non-rigid objects. Similar to the experimental setting shown in Section V-C1, we select all the 37 pedestrian video sequences from OTB-100 as the test set and show the tracking performances of comparing trackers in Figure 13.

According to the results shown in the Figure, one can observe a significant increase on accuracy (both for location precision and overlapping precision) after the pedestrian detector is used for correcting the tracking results. This indicates that for nonrigid objects, the proposed CODA strategy still performs well. On the other hand, the MD-Net and performs better than the CODA tracker with category information, at the cost of slow running speed (less than 1FPS).

VI. Conclusion and Future Work

In this work, we propose a simple yet effective algorithm to transferring the features in the classification domain to the visual tracking domain. The yielded visual tracker, termed CODA, is real-time and achieves the comparable tracking accuracies to the state-of-the-art deep trackers. To our best knowledge, CODA is the best-performing real-time visual tracker in the literature as far.

For a specific target category, CODA guides the visual tracking by the detection results. As the deep tracker and the deep detector share most part of the deep network, no much extra computation is required. Meanwhile, we can see a dramatic performance improvement in CODA, over its prototype, the HCF tracker. This improvement implies the absence of the target category could lead to poor tracking performance while to address this ambiguity in a sophisticated way could yield much better deep trackers.

Admittedly, updating the neural network online can lift the

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TCSVT.2019.2923639, IEEE Transactions on Circuits and Systems for Video Technology

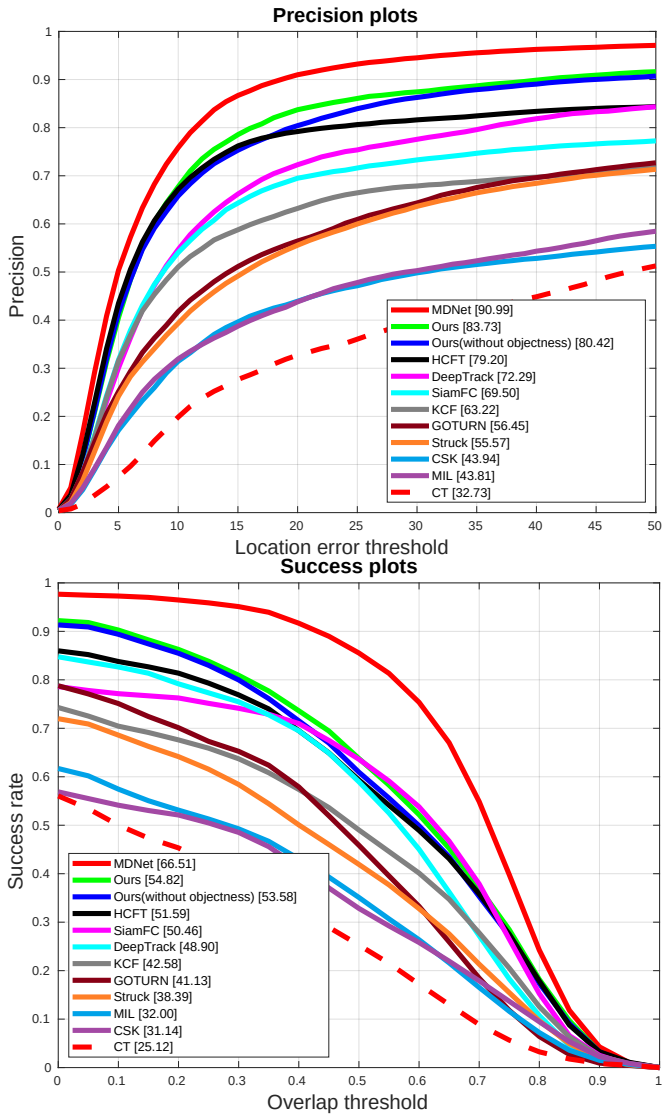


Fig. 13. The location error plots and the overlapping accuracy plots tested on the "pedestrian subset" of OTB-100. The comparing methods including MD-Net [6], HCF [5], the Siamese Tracker [8], GOTURN [7], CODA (this paper) and the shallow trackers.

tracking accuracy significantly [2], [6]. However, the existing online updating scheme results in dramatical speed reduction. One possible future direction could be to simultaneously update the KCF model and a certain part of the neural network (*e.g.* the last convolution layer). In this way, one could strike the balance between accuracy and efficiency and thus better tracker could be obtained.

Another possible direction is to involve more than one object categories in the corrective CNN branches for a certain type of tracking scenario. For instance, one can take pedestrian, car, bicycle and motorbike into consideration for road scene tracking. This could lead to even higher tracking robustness than the one-category CODA proposed in this paper.

REFERENCES

[1] Naiyan Wang and Dit-Yan Yeung. Learning a deep compact image representation for visual tracking. In *NIPS*, pages 809–817. 2013.

[2] Hanxi Li, Yi Li, and Fatih Porikli. Deeptrack: Learning discriminative feature representations online for robust visual tracking. *IEEE Transactions on Image Processing (TIP)*, 25(4):1834–1848, 2016.

[3] Anton Milan, Seyed Hamid Rezatofighi, Anthony Dick, Konrad Schindler, and Ian Reid. Online multi-target tracking using recurrent neural networks. *arXiv preprint arXiv:1604.03635*, 2016.

[4] Guanghan Ning, Zhi Zhang, Chen Huang, Zhihai He, Xiaobo Ren, and Haohong Wang. Spatially supervised recurrent convolutional neural networks for visual object tracking. *arXiv preprint arXiv:1607.05781*, 2016.

[5] Chao Ma, Jia-Bin Huang, Xiaokang Yang, and Ming-Hsuan Yang. Hierarchical convolutional features for visual tracking. In *ICCV*, pages 3074–3082, 2015.

[6] Hyeonseob Nam and Bohyung Han. Learning multi-domain convolutional neural networks for visual tracking. *arXiv preprint arXiv:1510.07945*, 2015.

[7] David Held, Sebastian Thrun, and Silvio Savarese. Learning to track at 100 fps with deep regression networks. *arXiv preprint arXiv:1604.01802*, 2016.

[8] Luca Bertinetto, Jack Valmadre, João F Henriques, Andrea Vedaldi, and Philip HS Torr. Fully-convolutional siamese networks for object tracking. In *ECCV*, pages 850–865, 2016.

[9] Xinyu Wang, Hanxi Li, Yi Li, Fumin Shen, and Fatih Porikli. Robust and real-time deep tracking via multi-scale domain adaptation. In *2017 IEEE International Conference on Multimedia and Expo (ICME)*, pages 1338–1343. IEEE, 2017.

[10] Hanxi Li, Yi Li, and Fatih Porikli. Deeptrack: Learning discriminative feature representations by convolutional neural networks for visual tracking. *BMVC*, 2014.

[11] Gao Zhu, Fatih Porikli, and Hongdong Li. Beyond local search: Tracking objects everywhere with instance-specific proposals. In *IEEE Conference on Computer Vision and Pattern Recognition*, pages 943–951, 2016.

[12] Naiyan Wang, Siyi Li, Abhinav Gupta, and Dit-Yan Yeung. Transferring rich feature hierarchies for robust visual tracking. *arXiv preprint arXiv:1501.04587*, 2015.

[13] Seunghoon Hong, Tackgeun You, Suha Kwak, and Bohyung Han. Online tracking by learning discriminative saliency map with convolutional neural network. In *ICML*, pages 597–606, 2015.

[14] K. Zhang, Q. Liu, Y. Wu, and M. H. Yang. Robust visual tracking via convolutional networks without training. *IEEE Transactions on Image Processing*, 25(4):1779–1792, 2015.

[15] K. Simonyan and A. Zisserman. Very deep convolutional networks for large-scale image recognition. *CoRR*, abs/1409.1556, 2014.

[16] Yao Sui, Ziming Zhang, Guanghui Wang, Yafei Tang, and Li Zhang. Real-time visual tracking: Promoting the robustness of correlation filter learning. In *ECCV*, pages 662–678, 2016.

[17] Xinyu Wang, Hanxi Li, Yi Li, Fatih Porikli, and Mingwen Wang. Deep tracking with objectness. In *2017 IEEE International Conference on Image Processing (ICIP)*, pages 660–664. IEEE, 2017.

[18] Ross Girshick, Jeff Donahue, Trevor Darrell, and Jitendra Malik. Rich feature hierarchies for accurate object detection and semantic segmentation. In *CVPR*, pages 580–587, 2014.

[19] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Spatial pyramid pooling in deep convolutional networks for visual recognition. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 37(9):1904–1916, 2014.

[20] Joseph Redmon, Santosh Divvala, Ross Girshick, and Ali Farhadi. You only look once: Unified, real-time object detection. *Computer Science*, pages 779–788, 2015.

[21] S. Ren, K. He, R Girshick, and J. Sun. Faster r-cnn: Towards real-time object detection with region proposal networks. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, pages 1–1, 2016.

[22] Wei Liu, Dragomir Anguelov, Dumitru Erhan, Christian Szegedy, and Scott Reed. Ssd: Single shot multibox detector. *arXiv preprint arXiv:1512.02325*, 2015.

[23] Kaiming He Jian Sun Jifeng Dai, Yi Li. R-FCN: Object detection via region-based fully convolutional networks. *arXiv preprint arXiv:1605.06409*, 2016.

[24] Sanghoon Hong, Byungseok Roh, Kye-Hyeon Kim, Yeongjae Cheon, and Minje Park. PVANet: Lightweight deep neural networks for real-time object detection. *arXiv preprint arXiv:1611.08588*, 2016.

[25] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. *arXiv preprint arXiv:1512.03385*, 2015.

[26] João F Henriques, Rui Caseiro, Pedro Martins, and Jorge Batista. High-speed tracking with kernelized correlation filters. *IEEE Transactions*

on Pattern Analysis and Machine Intelligence (TPAMI), 37(3):583–596, 2015.

[27] Olga Russakovsky, Jia Deng, Hao Su, Jonathan Krause, Sanjeev Satheesh, Sean Ma, Zhiheng Huang, Andrej Karpathy, Aditya Khosla, Michael Bernstein, Alexander C. Berg, and Li Fei-Fei. ImageNet Large Scale Visual Recognition Challenge. *International Journal of Computer Vision (IJCV)*, 115(3):211–252, 2015.

[28] Christian Szegedy, Wei Liu, Yangqing Jia, Pierre Sermanet, Scott Reed, Dragomir Anguelov, Dumitru Erhan, Vincent Vanhoucke, and Andrew Rabinovich. Going deeper with convolutions. In *CVPR*, pages 1–9, 2015.

[29] Yangqing Jia, Evan Shelhamer, Jeff Donahue, Sergey Karayev, Jonathan Long, Ross Girshick, Sergio Guadarrama, and Trevor Darrell. Caffe: Convolutional architecture for fast feature embedding. In *ACM MM*, pages 675–678, 2014.

[30] Jin Gao, Haibin Ling, Weiming Hu, and Junliang Xing. Transfer learning based visual tracking with gaussian processes regression. In *ECCV*, pages 188–203. 2014.

[31] Sam Hare, Amir Saffari, and Philip HS Torr. Struck: Structured output tracking with kernels. In *ICCV*, pages 263–270, 2011.

[32] Boris Babenko, Ming-Hsuan Yang, and Serge Belongie. Visual tracking with online multiple instance learning. *IEEE Transactions on Pattern Analysis and Machine Intelligence(TPAMI)*, pages 1619–1632, 2011.

[33] Zdenek Kalal, Jiri Matas, and Krystian Mikolajczyk. Pn learning: Bootstrapping binary classifiers by structural constraints. In *CVPR*, pages 49–56, 2010.

[34] Wei Zhong, Huchuan Lu, and Ming-Hsuan Yang. Robust object tracking via sparsity-based collaborative model. In *CVPR*, pages 1838–1845, 2012.

[35] Yi Wu, Jongwoo Lim, and Ming-Hsuan Yang. Online object tracking: A benchmark. In *CVPR*, pages 2411–2418, 2013.

[36] Yi Wu, Jongwoo Lim, and Ming-Hsuan Yang. Object tracking benchmark. *IEEE Transactions on Pattern Analysis and Machine Intelligence (TPAMI)*, 37(9):1834–1848, 2015.

[37] Matej Kristan, Roman Pflugfelder, Ale Leonardis, Jiri Matas, Fatih Porikli, Luka Cehovin, Georg Nebehay, Gustavo Fernandez, Toma Vojir, Adam Gatt, et al. The visual object tracking vot2013 challenge results. In *ICCV Workshops (ICCVW)*, pages 98–111, 2013.

[38] Matej Kristan, Roman Pflugfelder, Ale Leonardis, Jiri Matas, Luka ehovin, Georg Nebehay, Tom Voj, Gustavo Fernndez, Alan Lukei, and Aleksandar Dimitriev. The visual object tracking vot2014 challenge results. In *IEEE International Conference on Computer Vision Workshops*, pages 98–111, 2014.

[39] Michael Felsberg, Amanda Berg, Gustav Hager, Jorgen Ahlberg, Matej Kristan, Jiri Matas, Ale Leonardis, Luka Cehovin, Gustavo Fernandez, and Toma Vojir. The thermal infrared visual object tracking vot-tir2015 challenge results. In *IEEE International Conference on Computer Vision Workshop*, pages 639–651, 2015.

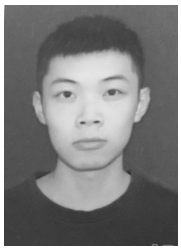
[40] Mark Everingham, Luc Van Gool, Christopher KI Williams, John Winn, and Andrew Zisserman. The pascal visual object classes (voc) challenge. *IJCV*, 88(2):303–338, 2010.

[41] Mark Everingham, S. M. Ali Eslami, Luc Van Gool, Christopher K. I. Williams, John Winn, and Andrew Zisserman. The pascal visual object classes challenge: A retrospective. *International Journal of Computer Vision*, 111(1):98–136, 2015.

[42] Navneet Dalal and Bill Triggs. Histograms of oriented gradients for human detection. In *CVPR*, volume 1, pages 886–893, 2005.

[43] Stefanos Zafeiriou, Cha Zhang, and Zhengyou Zhang. A survey on face detection in the wild: past, present and future. *Computer Vision and Image Understanding*, 138:1–24, 2015.

Hanxi Li is a Special Term Professor in the School of Computer and Information Engineering, Jiangxi Normal University, China. He was a Researcher at NICTA(Australia) from 2011-2015. He received his PhD from the Research School of Information Science and Engineering at the Australian National University, Canberra, Australia. His recent areas of interest include visual tracking, face recognition, and deep learning.



Xinyu Wang is currently a Master of Philosophy student with Australian Institute for Machine Learning (AIML), the University of Adelaide. His research interests include object detection, visual object tracking and deep learning.

Fumin Shen received the bachelors degree from Shandong University in 2007 and the Ph.D. degree from the Nanjing University of Science and Technology, China, in 2014. He is currently with the School of Computer Science and Engineering, University of Electronic Science and Technology of China. His major research interests include computer vision and machine learning. He was a recipient of the Best Paper Award Honorable Mention from ACM SIGIR in 2016 and ACM SIGIR in 2017 and the Worlds FIRST 10K Best Paper AwardPlatinum Award from the IEEE ICME in 2017.

Yi Li received the Ph.D. degree from the ECE Department, University of Maryland, College Park. He is a software engineer in Google Brain and X, the Moonshot Factory. He was a Senior Research Scientist with the Toyota Research Institute, a Senior Researcher with NICTA (Australia), and an Adjunct Fellow with Australian National University, Australia. He received the Best Student Paper of ICHFR, and the second price in the Semantic Robot Vision Challenge. He co-organized the first three DeepVision workshops in the IEEE Conference on Computer Vision and Pattern Recognition, and served as the Area Chair of the IEEE Winter Conference on Applications of Computer Vision in 2015 and 2016. He also co-founded a few robotics startups.

Fatih Porikli received the Ph.D. degree from New York University, New York,NY, USA, in 2002. He is currently a Professor with the Research School of Engineering, Australian National University, Canberra, ACT, Australia. He is also acting as a Chief Scientist at Huawei, Santa Clara, CA, USA. Previously, he led the Computer Vision Research Group at NICTA, and served as a Distinguished Research Scientist at Mitsubishi Electric Research Laboratories. Prof. Porikli is the recipient of the R&D 100 Scientist of the Year Award in 2006. He won 5 best paper awards at premier IEEE conferences and received 5 other professional prizes. He authored more than 200 publications and invented 73 patents. He is the co-editor of 2 books. He is currently the Associate Editor for five journals including the IEEE TRANSACTIONSON MULTIMEDIA and the IEEE SIGNAL PROCESSING MAGAZINE during the past 10 years. His research interests include computer vision,deep learning, manifold learning, online learning, and image enhancement with commercial applications in autonomous vehicles, video surveillance,consumer electronics, industrial automation, satellite and medical systems.

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TCSVT.2019.2923639, IEEE Transactions on Circuits and Systems for Video Technology

Mingwen Wang holds a Doctoral Degree (Ph.D.) in Computer Science from Shanghai Jiaotong University, China. His areas of research interest includes Machine Learning, Information Retrieval, Natural Language Processing, Image Processing, and Chinese Information Processing. At present he is working as Professor, School of Computer and Information Engineering, Jiangxi Normal University, China. He is member of various professional bodies including ACL, IEEE, CCF, and ACIS.

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TCSVT.2019.2923639, IEEE Transactions on Circuits and Systems for Video Technology

Fig. 14. Tracking results comparison on some key frames of 9 representative OTB-100 video sequences. The comparing methods include the proposed CODA tracker (green), GOTURN [7] (blue), Siamese tracker [8] (dashed yellow), HCF tracker [5] (dashed green) and the KCF algorithm [26] (dashed light blue). The red bounding boxes are the ground-truth locations of the tracking targets. Better view in color.