

# Online Object Tracking: A Benchmark

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## Abstract

*Object tracking is one of the most important components in numerous applications of computer vision. While much progress has been made in recent years with efforts on sharing code and datasets, it is of great importance to develop a library and benchmark to gauge the state of the art. In this work, we review recent advances of online object tracking and annotate image sequences with attributes for performance evaluation and analysis. We carry out large scale experiments with different evaluation criteria to understand how these algorithms perform. By analyzing quantitative results, we identify the critical components for a robust tracker and provide potential future research directions in this field.*

## 1. Introduction

Object tracking is one of the most important components in a wide range of applications in computer vision, such as surveillance, human computer interaction, and medical imaging [60, 12]. Given the initialized state (e.g., position) of a target object in the first frame of one video, the goal of tracking is to estimate the states of the target in the following frames. Although object tracking has been studied for several decades, and much progress has been made in recent years [28, 16, 47, 5, 40, 26, 19], it remains a very challenging problem. Numerous factors affect the performance of a tracking algorithm, such as illumination variation, occlusion, as well as background clutters, and there exists no single tracking approach that can successfully handle *all* scenarios. Therefore, it is crucial to evaluate the performance of state-of-the-art trackers to demonstrate their strength and weakness and help identify future research directions in this field for designing more robust algorithms.

For comprehensive performance evaluation, it is critical to collect a representative dataset. There exist several datasets for visual tracking in the surveillance scenarios, such as the VIVID [14], CAVIAR [21], and PETS databases. However, the target objects are usually humans or cars of small size in these surveillance sequences, and the background is usually static. Although some tracking dataset-

s [47, 5, 33] for generic scenes are annotated with bounding box, most of them are not. For sequences without labeled ground truth, it is difficult to evaluate tracking algorithms as the reported results are based on different annotated object locations. We build a dataset which consists of annotated sequences and attributes, to facilitate tracking evaluation. These attributes are defined by the factors that affect tracking performance, such as occlusion, fast motion, and illumination variation.

Recently, more tracking source codes have been made publicly available, e.g., the OAB [22], IVT [47], MIL [5], L1 [40], and TLD [31] algorithms, which have been commonly used for evaluation. However, the input and output formats of most trackers are different and thus it is inconvenient for large scale performance evaluation. In this work, we build a code library that includes most publicly available trackers to facilitate the evaluation task.

One common issue in assessing tracking algorithms is that the results are reported based on just a few sequences with different initial conditions or parameters. Thus, the results do not provide the holistic view of these algorithms. For fair and comprehensive performance evaluation, we propose to sample the initial conditions for tracking spatially and temporally given the ground-truth target locations. While the robustness to initialization is a well-known problem in the field, it is seldom addressed in the literature. To the best of our knowledge, this is the first comprehensive work to address and analyze the initialization problem of object tracking. We use the precision plots based on location error metric and the success plots based on the overlap metric, to analyze the performance of each algorithm.

The contribution of this work is three-fold:

**Dataset.** We build a tracking dataset with 50 fully annotated sequences to facilitate tracking evaluation.

**Code library.** We integrate most publicly available trackers in our code library with uniform input and output formats to facilitate large scale performance evaluation. At present, it includes 29 tracking algorithms.

**Robustness evaluation.** The initial bounding boxes for tracking are sampled spatially and temporally to evaluate the robustness and characteristics of trackers. Each tracker

is extensively evaluated and more than 660,000 bounding box results are got for analysis of each tracker.

This work mainly focuses on the online<sup>1</sup> tracking of single target. The code library, annotated dataset and all the tracking results will be made available to the public<sup>2</sup>.

## 2. Related Work

In this section, we review recent algorithms for object tracking in terms of several main modules: representation scheme, search mechanism, and model update. In addition, some methods have been proposed that build on combing some trackers or mining context information.

**Representation Scheme.** Object representation is one of major components in any visual tracker and numerous schemes have been presented [35]. Since the pioneering work of Lucas and Kanade [37, 8], *holistic* templates (raw intensity values) have been widely used for tracking [25, 39, 2]. Subsequently, subspace-based tracking approaches [11, 47] have been proposed to better account for appearance changes. Furthermore, Mei and Ling [40] propose a tracking approach based on sparse representation to handle the corrupted appearance and recently it has been further improved [41, 57, 64, 10, 55, 42]. In addition to template, many other visual features have been adopted in tracking algorithms, such as color histograms [16], histograms of oriented gradients (HOG) [17, 52], covariance region descriptor [53, 46, 56] and Haar-like features [54, 22]. Recently, the discriminative model has been widely adopted in tracking [15, 4], where a binary classifier is learned online to discriminate the target from the background. Numerous learning methods have been adapted to the tracking problem, such as SVM [3], structured output SVM [26], ranking SVM [7], boosting [4, 22], semi-boosting [23] and multi-instance boosting [5]. To make trackers more robust to pose variation and partial occlusion, an object can be represented by parts where each one is represented by descriptors or histograms. In [1] several *local* histograms are used to represent the object in a pre-defined grid structure. Kwon and Lee [32] propose an approach to automatically update the topology of local patches to handle large pose changes. To better handle appearance variations, some approaches regarding integration of multiple representation schemes have recently been proposed [62, 51, 33].

**Search Mechanism.** Deterministic or stochastic methods have been used to search for the target objects. When the tracking problem is posed within an optimization framework and the objective function is differentiable with respect to the motion parameters, gradient descent methods can be used to locate the target efficiently [37, 16, 20, 49]. However, the objective functions of the deterministic ap-

<sup>1</sup>Here, the word *online* means during tracking only the information of previous few frames is used for inference at any time instance.

<sup>2</sup>The website is <https://visual-tracking.net>

proaches are usually nonlinear and contain many local minima. To alleviate this problem, dense sampling methods have been adopted [22, 5, 26] at the expense of high computational load. On the other hand, stochastic search algorithms such as particle filters [28, 44] have been used to alleviate the local minimal problem without high computational load. Recent methods based on particle filters are developed with effective observation models [47, 40, 30].

**Model Update.** It is crucial to update the target representation or model to account for appearance variations, and much attention has been paid in recent years to address this issue. Matthews *et al.* [39] address the template update problem for the Lucas-Kanade algorithm [37] where the template is updated with the combination of the fixed reference template extracted from the first frame and the result from the most recent frame. Effective update algorithms have also been proposed via online mixture model [29], online boosting [22], and incremental subspace update [47]. For discriminative model, recently much attention has been paid to improve the sample collection part to make the online trained classifier more robust [23, 5, 31, 26]. While much progress has been made, it is still difficult to get an adaptive appearance model to avoid drifts.

**Context and Fusion of Trackers.** Context information is also very important for tracking. Recently some approaches have been proposed by mining auxiliary objects or local visual information surrounding the target to assist tracking [59, 24, 18]. The context information is especially helpful when the target is fully occluded or outside of the image region [24]. To improve the tracking performance, some tracker fusion methods have been proposed recently. Santner *et al.* [48] propose an approach that combines static, moderately adaptive and highly adaptive trackers to account for appearance changes. Multiple trackers are sampled and selected in a Bayesian framework to better account for appearance changes [34] or with multiple features [61].

## 3. Evaluated Algorithms and Datasets

For fair evaluation, we test the tracking algorithms whose original source or binary codes are publicly available as all implementations inevitably involve technical details and specific parameter settings<sup>3</sup>. Table 1 shows the evaluated tracking algorithms. We also evaluate the trackers in the VIVID testbed [14] including the mean shift (MS-V), template matching (TM-V), ratio shift (RS-V) and peak difference (PD-V) methods.

In recent years, many benchmark datasets have been developed for various vision problems, such as the Berkeley segmentation [38], FERET face recognition [45] and optical flow dataset [9]. There exist some datasets for the tracking in the surveillance scenario, such as the VIVID [14] and

<sup>3</sup>Some source codes [36, 58] are obtained from direct contact, and some methods are implemented on our own [44, 16].

Method	Representation	Search	MU	Code	FPS
CPF [44]	L, IH	PF	N	C	109
LOT [43]	L, color	PF	Y	M	0.70
IVT [47]	H, PCA, GM	PF	Y	MC	33.4
ASLA [30]	L, SR, GM	PF	Y	MC	8.5
SCM [65]	L, SR, GM+DM	PF	Y	MC	0.51
L1APG [10]	H, SR, GM	PF	Y	MC	2.0
MTT [64]	H, SR, GM	PF	Y	M	1.0
VTD [33]	H, SPCA, GM	MCMC	Y	MC-E	5.7
VTS [34]	L, SPCA, GM	MCMC	Y	MC-E	5.7
LSK [36]	L, SR, GM	LOS	Y	M-E	5.5
ORIA [58]	H, T, GM	LOS	Y	M	9.0
DFT [49]	L, T	LOS	Y	M	13.2
KMS [16]	H, IH	LOS	N	C	3,159
SMS [13]	H, IH	LOS	N	C	19.2
VR-V [15]	H, color	LOS	Y	MC	109
Frag [1]	L, IH	DS	N	C	6.3
OAB [22]	H, Haar, DM	DS	Y	C	22.4
SemiT [23]	H, Haar, DM	DS	Y	C	11.2
BSBT [50]	H, Haar, DM	DS	Y	C	7.0
MIL [5]	H, Haar, DM	DS	Y	C	38.1
CT [63]	H, Haar, DM	DS	Y	MC	64.4
TLD [31]	L, BP, DM	DS	Y	MC	28.1
Struck [26]	H, Haar, DM	DS	Y	C	20.2
CSK [27]	H, T, DM	DS	Y	M	362
CXT [18]	H, BP, DM	DS	Y	C	15.3

Table 1. Evaluated tracking algorithms (MU: model update, FPS: frames per second). For representation schemes, L: local, H: holistic, T: template, IH: intensity histogram, BP: binary pattern, PCA: principal component analysis, SPCA: sparse PCA, SR: sparse representation, DM: discriminative model, GM: generative model. For search mechanism, PF: particle filter, MCMC: Markov Chain Monte Carlo, LOS: local optimum search, DS: dense sampling search. For the model update, N: No, Y: Yes. In the Code column, M: Matlab, C: C/C++, MC: Mixture of Matlab and C/C++, suffix E: executable binary code.

CAVIAR [21] datasets. For generic visual tracking, more sequences have been used for evaluation [47, 5]. However, most released sequences do not have the annotations or ground truth, and the quantitative evaluation results may be generated with different initial conditions. To facilitate fair performance evaluation, we collect and annotate most commonly used tracking sequences. Figure 1 shows the first frame of each sequence where the target object is initialized with a bounding box.

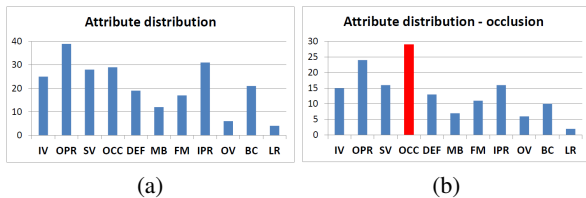


Figure 2. Attribute distribution. In the attribute distribution of occlusion subset, the dominate attribute is marked as red.

**Attributes of tracking sequence.** Evaluating trackers is difficult because many factors affect the tracking performance. For better evaluating and analyzing the strength and weakness of tracking approaches we propose to anno-

tate the sequences with the following 11 attributes: illumination variation (**IV**): the illumination in the target region is changed; scale variation (**SV**): the ratio of the bounding boxes of the first frame and the current frame is not less than  $t_s$  ( $\geq 1$ ) or not more than  $1/t_s$  ( $t_s=2$  in this work); occlusion (**OCC**): the target is partially or fully occluded; deformation (**DEF**): non-rigid object deformation; motion blur (**MB**): the target region is blurred due to the motion of target or camera; fast motion (**FM**): the motion computed from the ground truth is larger than  $t_m$  pixels ( $t_m=20$  in this work); in-plane rotation (**IPR**): the target rotates in the image plane; out-of-plane rotation (**OPR**): the target rotates out of the image plane; out-of-view (**OV**): one portion of the target leaves the view of camera; background clutters (**BC**): the background near the target has the similar color or texture as the target; low resolution (**LR**): the number of pixels inside the ground-truth bounding box is less than  $t_r$  ( $t_r=400$  in this work).

The attribute distribution in our dataset is shown in Figure 2(a). Some attributes occur more frequently, e.g., OPR and IPR, than others. It also shows that one sequence is often annotated with several attributes. Aside from summarizing the performance on the whole dataset, we also construct several subsets corresponding to attributes to report specific challenging conditions. For example, the OCC subset contains 29 sequences which can be used to analyze the performance of trackers to handle occlusion. The attribute distributions in OCC subset is shown in Figure 2(b) and others are available in the supplemental material.

## 4. Evaluation Methodology

In this work, we use the precision and success rate for quantitative analysis. In addition, we evaluate the robustness of tracking algorithms in two aspects.

**Precision plot.** One widely adopted evaluation metric is the center location error, which is defined as the Euclidean distance between the center locations of the tracked target and the manually labeled ground truth. Then the average center location error over all the frames of one sequence is used to summarize the overall performance for that sequence. However, when the tracker loses the target, the output bounding box can be random so that sometimes the average error value may not measure the tracking performance correctly [6]. Recently the precision plot [6, 27] has been adopted to summarize the tracking performance. It shows the percentage of frames for which the estimated object location is within some threshold distance of the ground truth. Therefore, we use the precision plot in this work. To summarize a precision plot, we choose the threshold 20 and report the precision at this point in the curve [6].

**Success plot.** Another evaluation metric is the bounding box overlap. Given the tracked bounding box  $r_t$  and the ground truth bounding box  $r_a$ , the overlap score is defined



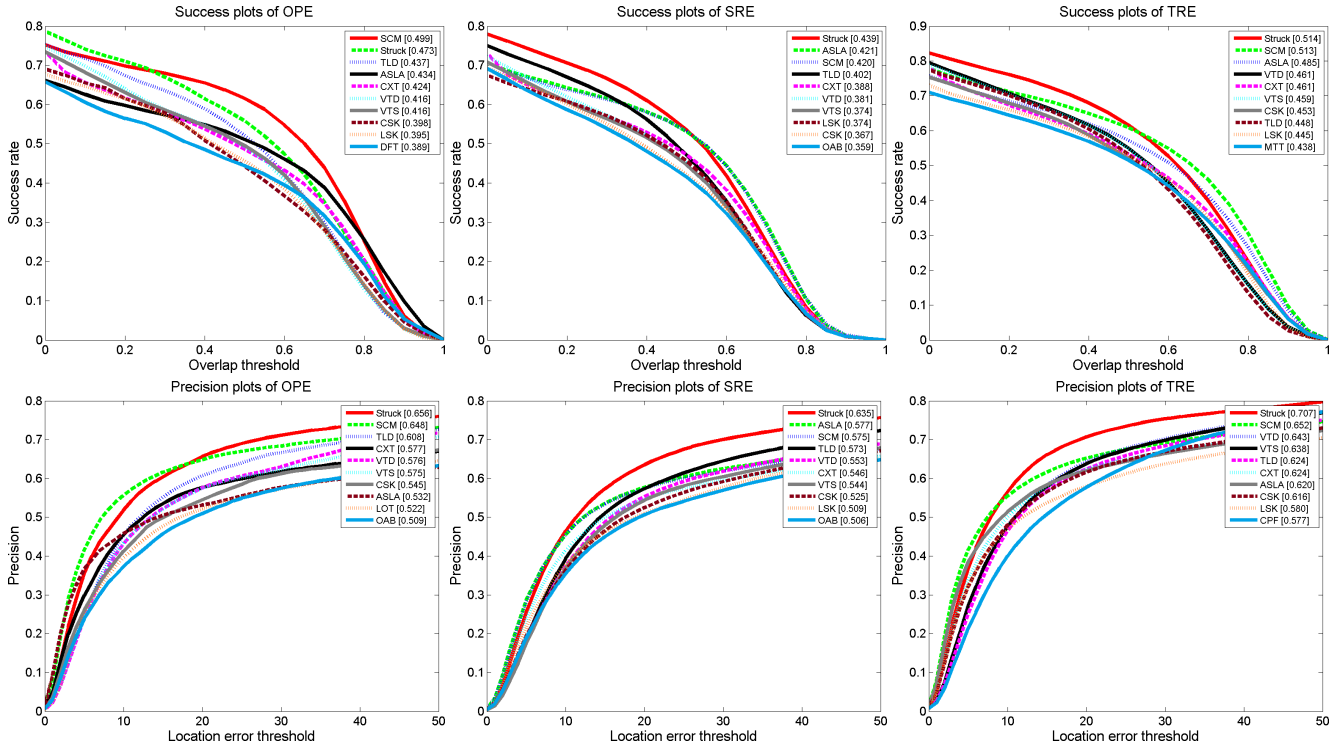


Figure 3. Plots of OPE, SRE, and TRE. The performance score for each tracker is shown in the legend. For each figure, the top 10 trackers are presented for clarity and complete plots are in the supplementary material (best viewed on high-resolution display).

ure 3 where only the top 10 algorithms are presented for clarity and the complete plots are displayed in the supplementary material. For success plots, we use AUC scores to summarize and rank the trackers, while for precision plots we use the results at error threshold of 20 for ranking. In the precision plots, the rankings of some trackers are slightly different from the rankings in the success plots in that they are based on different metrics which measure different characteristics of trackers. Because the AUC score of success plot measures the overall performance which is more accurate than the score at one threshold of precision plot, in the following we mainly analyze the rankings based on success plots but use the precision plots as auxiliary.

The average TRE performance is higher than that of OPE in that the number of frames decreases from the first to last segment of TRE. As the trackers tend to perform well in shorter sequences, the average of all the results in TRE tend to be higher. On the other hand, the average performance of SRE is lower than that of OPE. The initialization errors tend to cause trackers to update with imprecise appearance information, thereby causing gradual drifts.

In the success plots, the top ranked tracker SCM in OPE outperforms Struck by 2.6% but is 1.9% below Struck in SRE. The results also show that OPE is not the best performance indicator as the OPE is one trial of SRE or TRE. The ranking of TLD in TRE is lower than OPE and SRE. This is because TLD performs well in long sequences with a re-detection module while there are numerous short segments

in TRE. The success plots of Struck in TRE and SRE show that the success rate of Struck is higher than SCM and ALSA when the overlap threshold is small, but less than SCM and ALSA when the overlap threshold is large. This is because Struck only estimates the location of target and does not handle scale variation.

Sparse representations are used in SCM, ASLA, LSK, MTT and L1APG. These trackers perform well in SRE and TRE, which suggests sparse representations are effective models to account for appearance change (e.g., occlusion). We note that SCM, ASLA and LSK outperform MTT and L1APG. The results suggest that local sparse representations are more effective than the ones with holistic sparse templates. The AUC score of ASLA decreases less than the other top 5 trackers from OPE to SRE and the ranking of ASLA also increases. It indicates the alignment-pooling technique adopted by ASLA is more robust to mis-alignments and background clutters.

Among the top 10 trackers, CSK has the highest speed where the proposed circulant structure plays a key role. The VTD and VTS methods adopt mixture models to improve the tracking performance. Compared with other higher ranked trackers, the performance bottleneck of them can be attributed to their adopted representation based on sparse principal component analysis, where the holistic templates are used. Due to the space limitation, the plots of SRE are presented for analysis in the following sections, and more results are included in the supplement.

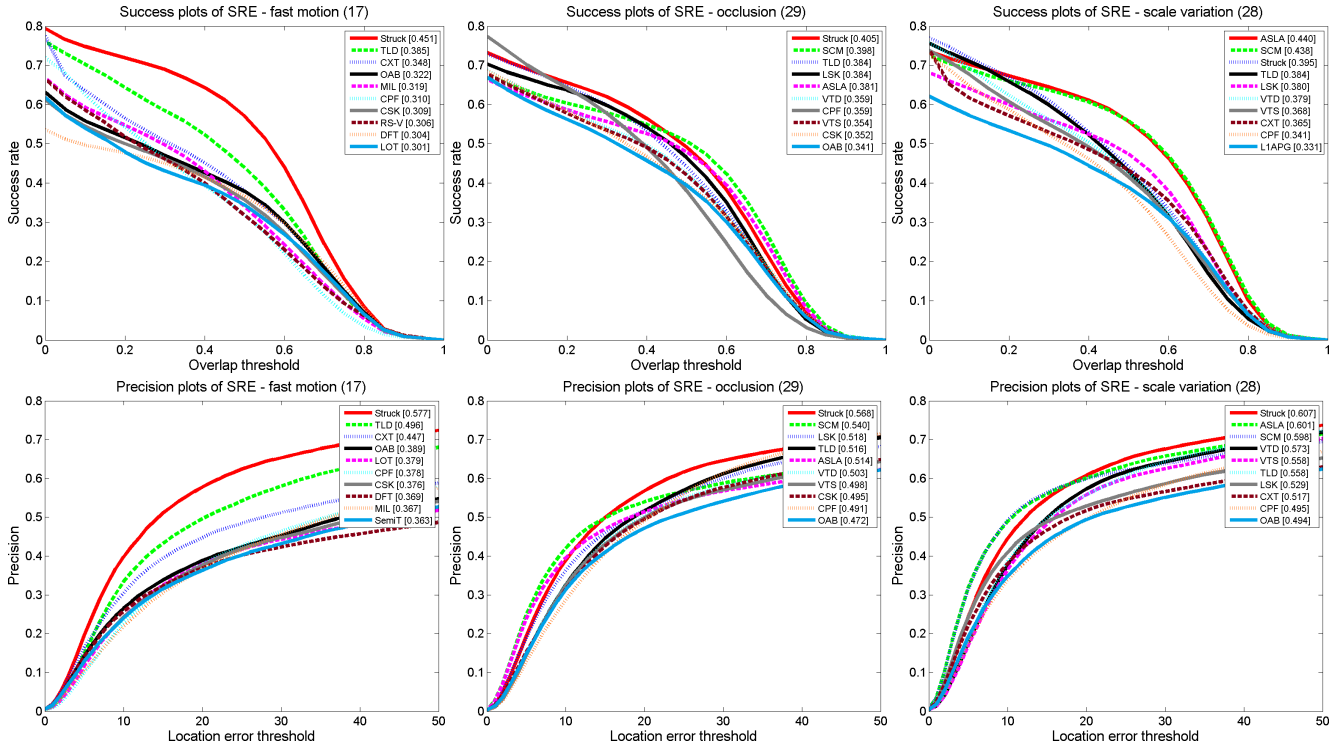


Figure 4. Plots for OCC, SV, and FM subsets. The value appears in the title is the number of sequences in that subset. Only the top 10 trackers are presented for clarity and complete plots are in the supplementary material (best viewed on high-resolution display).

## 5.2. Attribute-based Performance Analysis

By annotating the attributes of each sequence, we construct subsets with different dominant attributes which facilitates analyzing the performance of trackers for each challenging factor. Due to space limitations, we only illustrate and analyze the success plots and precision plots of SRE for attributes OCC, SV, and FM as shown in Figure 4, and more results are presented in the supplementary material.

When an object moves fast, dense sampling based trackers (e.g., Struck, TLD and CXT) perform much better than others. One reason is that the search ranges are large and the discriminative models are able to discriminate the targets from the background clutters. However, the stochastic search based trackers with high overall performance (e.g., SCM and ASLA) do not perform well in this subset due to the poor dynamic models. If these parameters are set to large values, more particles are required to make the tracker stable. These trackers can be further improved with dynamic models with more effective particle filters.

On the OCC subset, the Struck, SCM, TLD, LSK and ASLA methods outperform others. The results suggest that structured learning and local sparse representations are effective in dealing with occlusions. On the SV subset, ASLA, SCM and Struck perform best. The results show that trackers with affine motion models (e.g., ASLA and SCM) often handle scale variation better than others that are designed to account for only translational motion with a few

exceptions such as Struck.

## 5.3. Initialization with Different Scale

It has been known that trackers are often sensitive to initialization variations. Figure 5 and Figure 6 show the summarized tracking performance with initialization at different scales. When computing the overlap score, we rescale the tracking results so that the performance summary could be comparable with the original scale, i.e., the plots of OPE in Figure 3. Figure 6 illustrates the average performance of all trackers for each scale which shows the performance often decreases significantly when the scale factor is large (e.g.,  $\times 1.2$ ) as many background pixels are inevitably included in the initial representations. The performance of TLD, CXT, DFT and LOT decreases with the increase of initialization scale. This indicates these trackers are more sensitive to background clutters. Some trackers perform better when the scale factor is smaller, such as L1APG, MTT, LOT and CPF. One reason for this in the case of L1APG and MTT is that the templates have to be warped to fit the size of the usually smaller canonical template so that if the initial template is small, more appearance details will be kept in the model. On the other hand, some trackers perform well or even better when the initial bounding box is enlarged, such as Struck, OAB, SemiT, and BSBT. This indicates that the Haar-like features are somewhat robust to background clutters due to the summation operations when computing features. Overall, Struck is less sensitive to scale

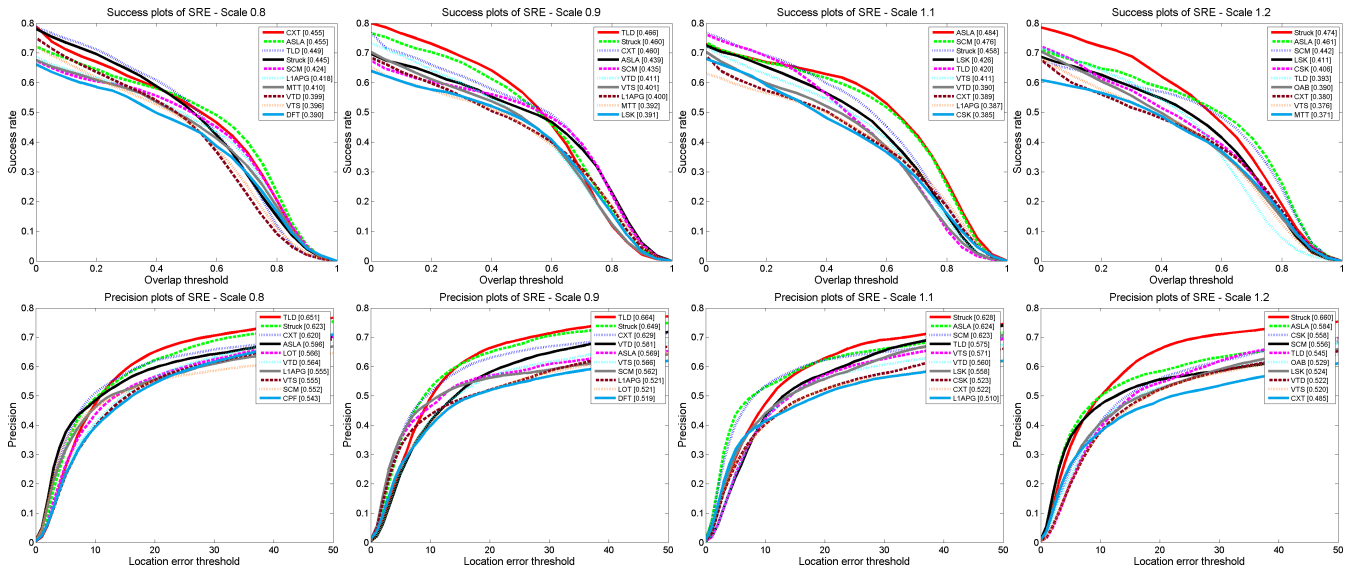


Figure 5. SRE of the trackers initialized with different bounding box sizes. The value on top of each figure is the scale factor. For each figure, the top 10 trackers are presented for clarity and complete plots are in the supplementary material.

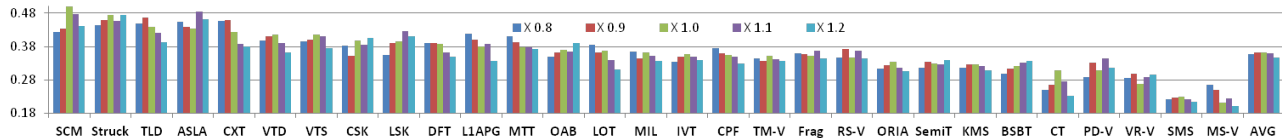


Figure 6. Performance summary for the trackers initialized with different size of bounding box. AVG (the last one) illustrates the average performance over all trackers for each scale.

variation than other well-performing methods.

## 6. Concluding Remarks

In this paper, we carry out large scale experiments to evaluate the performance of recent online tracking algorithms. Based on our evaluation results and observations, we highlight some tracking components which are essential for improving tracking performance. First, background information is critical for effective tracking. It can be exploited by using advanced learning techniques to encode the background information in the discriminative model implicitly (e.g., Struck), or serving as the tracking context explicitly (e.g., CXT). Second, local models are important for tracking as shown in the performance improvement of local sparse representation (e.g., ASLA and SCM) compared with the holistic sparse representation (e.g., MTT and LIAPG). They are particularly useful when the appearance of target is partially changed, such as partial occlusion or deformation. Third, motion model or dynamic model is crucial for object tracking, especially when the motion of target is large or abrupt. However, most of our evaluated trackers do not focus on this component. Good location prediction based on the dynamic model could reduce the search range and thus improve the tracking efficiency and robustness. Improving these components will further advance the state of the art of online object tracking.

The evaluation results show that significant progress in

the field of object tracking has been made in the last decade. We propose and demonstrate evaluation metrics for in-depth analysis of tracking algorithms from several perspectives. This large scale performance evaluation facilitates better understanding of the state-of-the-art online object tracking approaches, and provides a platform for gauging new algorithms. Our ongoing work focuses on extending the dataset and code library to include more fully annotated sequences and trackers.

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