Beyond standard benchmarks: Parameterizing performance evaluation in visual object tracking

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Abstract

Benchmarks have played an important role in advancing the field of visual object tracking. Due to weakly defined and sometimes biased attribute specification, existing benchmarks do not allow fine-grained tracker analysis with respect to specific attributes. Apart from illumination changes and occlusions, the tracking performance is most strongly affected by the object motion. In this paper, we propose a novel approach for tracker evaluation with respect to the motion-related attributes. Our approach utilizes 360 degree videos to generate realistic annotated short-term tracking scenarios with exact specification of the object motion type and extent. A fully annotated dataset of 360 degree videos was constructed and fine-grained performance of 17 state-of-the-art trackers is reported. The proposed approach offers unique tracking insights, is complementary to existing benchmarks, and will be made publicly available. The evaluation system was implemented within a state-of-the-art performance evaluation toolkit and supports straight-forward extension with third-party trackers.

1. Introduction

Single-target visual object tracking has made significant progress in the last decade. To a large extent this can be attributed to the adoption of benchmarks, through which common evaluation protocols, datasets and baseline algorithms have been established. Starting with PETS initiative [28] in 2005, several benchmarks on general single-target short-term tracking have been developed since, most notably OTB50 [25], VOT2013 [15], ALOV300+ [21], VOT2014 [16, 14], OTB100 [26], TC128 [17] and VOT2016 [12].

A recent work on test-data validation in computer vision [29] argued that dataset variation, systematic organization and low redundancy are crucial for practical evaluation. The existing benchmarks address this by increasing the number of sequences [21], applying advanced dataset construction methodologies [12] and by annotating entire sequences or even individual frames with visual attributes [26, 14].

Figure 1: Generating view frames from a 360 degree source sequence. Manipulation of the camera parameters enables accurate parametrization of motion types in the generated viewpoint sequences.

Annotation of frames (sometimes entire sequences) with multiple attribute labels prohibits accurate attribute-wise analysis due to the attribute cross-talk. Moreover, the attribute labels are typically subject to human bias and are merely binary annotations without accurate parametrization. Such parametrization is possible through computer graphics generated sequences [9, 13], however the level of realism in object motion and appearance in such sequences still presents a limitation for performance evaluation of general tracking methods.
The recent benchmarks \cite{12,18} report that, apart from the obvious situations like full occlusions, the trackers’ performance is largely affected by the object motion with respect to the camera. In fact, in many applications, such as drone tracking, performance varies mainly with respect to scale changes and fast motion \cite{13}. Detailed analyses of these important motion attributes in existing benchmarks remain limited due to a limited size of datasets, lack of accurate attribute annotation, and lack of full camera control during sequence acquisition.

This paper addresses the aforementioned limitations of the existing benchmarks by proposing a framework for parametrization of motion related attributes. We consider omnidirectional 360 degree videos as prerecorded proxy representations of 3D world that capture photo-realism of standard benchmarks. The framework offers a high degree of virtual camera control, which has so far been possible only in computer graphics generated sequences. Our approach focuses on detailed analysis of motion attributes and, at this point, we do not evaluate performance under occlusions and illumination changes. In this respect our approach complements the existing benchmarks in this important class of sequence attributes.

**Contributions.** The first contribution is a new motion-type performance evaluation paradigm and a new method to generate realistic sequences with high degree of motion parametrization. We introduce a virtual camera model that utilizes 360 degree videos to generate realistic annotated short-term tracking scenarios (Figure 1). The exact specification of parameterized motion types in the sequences guarantees a clear causal relation between the generated motions and the tracking performance change. This allows for a fine-grained performance analysis that goes far beyond the capabilities of existing benchmarks. As part of the contribution, a parameterized sequence generator is developed using a popular performance evaluation toolkit \cite{12}. The generator is highly extendable and compatible with the existing evaluation protocols.

The second major contribution is a new motion benchmark for short-term single-target trackers, MoBe2016. We have constructed a dataset of annotated 360 degree videos adding up to 17537 frames, defined twelve motion types and evaluated 17 state-of-the-art trackers from recent benchmarks \cite{26,12}. The new benchmark, the results and the corresponding software will be made publicly available and are expected to significantly affect future developments in single-target tracking.

The paper is organized as follows. Section 2 contains a review of related work, Section 3 describes our sequence parameterization approach, Section 4 presents the proposed benchmark, Section 5 contains presentation of results, and Section 6 contains discussion and concluding remarks.

## 2. Related work

Modern short-term tracking benchmarks \cite{26,15,14,13,12,21,18} acknowledge the importance of motion related attributes and support evaluation with respect to these. However, the evaluation capability significantly depends on the attribute presence and distribution, which is often related to the sequence acquisition. In application-oriented benchmarks like \cite{13} the attribute distribution is necessarily skewed by the application domain. Some general benchmarks \cite{26,21} thus include a large number of sequences from various domains. But since the sequences are post-hoc annotated, the dataset diversity is not guaranteed. A recent benchmark \cite{12} addressed this by considering the attributes already at the sequence collection stage and applied an elaborate methodology for automatic dataset construction.

The strength of per-attribute evaluation depends on the annotation approach. In most benchmarks \cite{26,21,18} all frames are annotated by an attribute even if it occupies only a part of the sequence. Kristan et al. \cite{14} argued that this biases per-attribute performance towards average performance and proposed a per-frame annotation to reduce the bias. However, a single frame might still contain several attributes, resulting in the attribute cross-talk bias.

The use of computer graphics in training and evaluation has recently been popularized in computer vision. Mueller et al. \cite{13} propose online virtual worlds creation for drone tracking evaluation, but using only a single type of the object, without motion parametrization and low level of realism. Vig et al. \cite{9} address the virtual worlds realism levels and ambient parametrization learning and performance evaluation, however, just for vehicle detection.

### 2.1. Comparison with our new motion benchmark

A comparison of our proposed MoBe2016 with related benchmarks is summarized in Table 1. The values under MAC indicate the percentage of frames in the dataset with at least a single motion attribute. The motion attributes are most frequent in the MoBe (100% coverage) and UAV123 \cite{18} (96% coverage). To reflect the dataset size in motion evaluation, we compute the number of effective frames per attribute (FPA). This measure counts the number of frames that contain a particular motion attribute, where each frame contributes with weight inversely proportional to the number of motion attributes it contains. The FPA is highest for an application-specific UAV123 \cite{18} (27107). Among the general tracking benchmarks, this value is highest for the proposed MoBe2016 (17537), which exceeds the second largest (OTB100 \cite{26}) by over 30%.

The FPA alone does not fully reflect the evaluation strength since it does not account for the attribute cross-talk. A lower bound on the cross-talk is reflected by the INTER measure that shows a percentage of motion-annotated frames with at least two motion attributes. The measure
shows that well over half of the frames in UAV123 [18] (78%) and OTB100 [26] (63%) suffer from the attribute cross-talk. The cross-talk is lowest for the proposed MoBe2016 (0%), ALOV [21] (0%) and VOT2016 [12] (32%).

On average, most existing benchmarks are annotated by four motion types. The proposed MoBe2016 contains approximately three times more motion types than existing benchmarks. The existing benchmarks lack motion type quantification (e.g., the extent of speed in attribute fast motion), which results in inconsistent definitions across benchmarks. In contrast, the motion types are objectively defined through their parametrization in the proposed MoBe2016.

Table 1: Comparison of MoBe2016 with popular recent tracking benchmarks: ALOV300+ [21], OTB100 [26], UAV123 [18] and VOT2016 [12]. Best, second best and third best values are shown in red, blue and green, respectively.

| Dataset             | 21  | 26  | 18  | 12  | MoBe |
|---------------------|-----|-----|-----|-----|------|
| MAC (%)             | 19  | 88  | 96  | 61  | 100  |
| FPA                 | 4275| 12929| 27107| 4366| 17537|
| INTER (%)           | 0   | 63  | 78  | 32  | 0    |
| Motion classes      | 3   | 3   | 3   | 3   | 6    |
| Motion types        | 4   | 4   | 4   | 3   | 12   |
| Parameterized       | no  | no  | no  | no  | yes  |
| Per-frame           | no  | no  | no  | yes | yes  |

3. Sequence parametrization

Two key concepts are introduced by our motion evaluation methodology: a source sequence and a viewpoint sequence. A source sequence is an omnidirectional video that simultaneously captures 360 degree field of view. The video is stored as a projection onto a spectator-centered sphere, i.e., $S = \{S_t\}_{t=1:N}$, where $S_t$ is a projection at frame $t$. Such representation allows to generate arbitrary views of a 3D scene from the point of observation.

A viewpoint sequence is a sequence of images obtained from a spherical representation by projection into a pinhole camera, i.e., $I = \{I_t\}_{t=1:N}$. The camera model has adjustable rotation and focal length parameters, thereby defining the state of the camera at time $t$ as

$$C_t = [\alpha_t, \beta_t, \gamma_t, f_t],$$

where the first three parameters are the Euler angles and $f_t$ denotes the focal length. Each frame in a viewpoint sequence is therefore the result of the corresponding image in the source sequence and the camera parameters, i.e. $I_t = p_{\text{cam}}(S_t; C_t)$.

The ground truth object state in each frame is specified in a viewpoint-agnostic spherical coordinate system, i.e., $A = \{A_t\}_{t=1:N}$. Following the VOT Challenge protocol [14] the state is defined as a rectangle using four-points $A_t = \{\theta_t, \rho_t\}_{t=1:4}$. Given a pinhole camera viewpoint parameters $C_t$, the ground truth $A_t$ is projected into the image plane by projective geometry, i.e., $G_t = p_{\text{gl}}(A_t; C_t)$.

The camera parameters $C_t$ are continually adjusted during the creation of the viewpoint sequence to keep the projected object within the field of view, thus satisfying the short-term tracking constraint. The camera viewpoint is adjusted via a camera controller $p_{\text{con}}(\cdot, \cdot)$ that applies a prescribed motion type $E$ and maps the object ground truth state into camera parameters while satisfying the short-term tracking constraint, i.e.,

$$p_{\text{con}}(A_t, E, t) \mapsto C_t,$$  \hspace{1cm} (2)

Depending on the motion type specification, the controller generates various apparent object motions.

3.1. Motion type evaluation framework

The evaluation framework implements the VOT supervised evaluation mode [6] and the VOT [14] performance evaluation protocol, which allows full use of long sequences. In this evaluation mode, a tracker is initialized and re-set upon drifting off the target. Stochastic trackers are run multiple times and the results are averaged.
erate one frame at a time from the 360 degree source sequence, as well as the ground truth annotations and the camera controller motion type parameters. The sequence and the 2D ground truth are therefore generated on the fly during the valuation and are reproducible for each time-step. The communication between the the evaluator and the tracker is implemented through the state-of-the-art TraX [22] communication protocol. Our motion type evaluation framework is summarized in Figure 2.

4. Motion benchmark—MoBe2016

Our motion parametrization framework is demonstrated on a novel single-target visual object tracking motion benchmark (MoBe2016). The benchmark contains a library of 17 state-of-the-art trackers, twelve motion types and a dataset of 360 degree source sequences. The dataset, the motion types, the trackers tested and the performance measures are explained next.

4.1. Dataset acquisition

The new dataset contains fifteen 360 degree videos with an average video length of 1169 frames, amounting to 17537 frames. The videos were mostly selected from a large collection of 360 degree videos available on YouTube. To maximize the target diversity, we recorded additional sequences using Ricoh Theta 360 degree camera. Videos were converted to a cube-map projection and encoded with MP4 H.264 codec. Each frame of the video was manually annotated by a rectangular region encoded in spherical coordinates using an annotation tool specifically designed for this use case. Some of the viewpoint frame examples of individual source sequences are shown in Figure 3.

![Figure 3: A preview of sequences in the dataset from the view that centers the target.](image)

4.2. Motion types specification

We consider six motion classes that reflect typical dynamic relations between an object (target) and a camera:

- **Stabilized setup**, denoted as $E_b$, keeps the object at image center and adjusts the camera distance to keep the object diagonal constant at 70 pixels. A variant with a diagonal constant at 35 pixels is considered as well to test tracking objects from far away, $E_{sb}$.
- **Centered rotation setup**, denoted as $E_r$, fixes the object center and the scale as $E_b$ and then rotates the camera around the optical axis. Two variants, with low and high rotation speeds, $E_{sr}$ and $E_{fr}$, respectively, are considered.
- **Displaced rotation setup**, denoted as $E_d$, displaces the object center and then rotates the camera around its optical axis.
- **Scale change setup**, denoted as $E_s$, fixes the center and then periodically changes the scale by a cosine function with amplitude oscillation around the nominal scale of $E_b$. Two variants, i.e., with a low, $E_{ss}$, and a high frequency, $E_{fs}$, but equally moderate amplitude are considered. Another variant with a moderate frequency but large amplitude, $E_{ws}$, is considered as well.
- **Planar motion setup**, denoted as $E_m$, displaces the camera from the object center and performs circular motion in image plane. A variant with low – $E_{sm}$ and high – $E_{fm}$ frequency are considered.
- **Translation noise setup**, denoted as $E_n$, fixes the center and the scale as in $E_b$ then randomly displaces the center by drawing a displacement vector from a normal distribution. Two variants, one with small, $E_{sn}$, and one with large, $E_{ln}$, noise are considered.

The variations of six motion classes result in 12 different motion types, which are illustrated in Figure 4; for exact values of motion parameters please see Supplementary material. Note that each 360 degree video in our dataset creates a sequence with specific motion parameters. Thus each motion type is evaluated on all frames with only a single (quantitatively defined) motion type per frame present.

4.3. Trackers tested

A set of 17 trackers was constructed by considering baseline and top-performing representatives on recent benchmarks [26, 12] from the following 6 broad classes of trackers. (1) **Baselines** include standard discriminative and generative trackers MIL [2], CT [31], IVT [20], and FragTrac [11], a state-of-the-art mean-shift tracker ASMS [24], and Struck SVM tracker [10]. (2) **Correlation filters** include the standard KCF [11] and three top-performing correlation filters on VOT2016 [12] – DSST [7], Staple [4] and SRDCF [8]. (3) **Sparse trackers** include top-performing sparse trackers L1APG [3] and ASLA [27]. (4) **Part-based trackers** include the recent state-of-the-art CMT [19].
LGT [32], FoT [23]. In addition, the set comprises a state-of-the-art (5) Hybrid tracker MEEM [30] and (6) ConvNet tracker SiamCF [5].

4.4. Performance measures

The tracking performance is measured by the VOT [13] measures: tracker accuracy (A), robustness (R) as well as the expected average overlap (EAO). The accuracy measures the overlap between the output of the tracker and the ground truth bounding box during periods of successful tracking, while the robustness measures the number of times a tracker failed and required re-initialization [6]. The expected average overlap score is an estimator of the average overlap on a typical short-term sequence a tracker would obtain without reset [13]. All scores are calculated on per-sequence basis and averaged with weights proportional to the sequence length.

5. Results

The 17 trackers were evaluated on a total of 210,444 frames containing various motion types, which makes this the largest fine-grained motion-related tracker evaluation to date. Results are summarized by A-R plots (Figure 5), general performance graphs (Figure 6, Figure 7) and in Table 2. In the following we discuss performance with respect to various motion classes and types.

Scale adaptation: Slow scale changes ($E_s^s$) are addressed best by correlation filters that apply scale adaptation (i.e., KCF, DSST, Staple, SRDCF). Their performance is not significantly affected as long as the change is gradual enough, even for large amplitudes ($E_w^s$). However, fast changes ($E_f^s$) significantly reduce performance, implying that the number of scales explored should be increased in these trackers. The ConvNet tracker SiamCN does not suffer from this discrepancy, which is likely due to a large set of scales it explores. The difference in performance drop for fast ($E_f^s$) and large ($E_w^s$) scale change is low for scale-adaptive mean shift ASMS and part-based trackers (i.e., CMT, FoT and LGT). In contrast to correlation filters, these trackers do not greedily explore the scale space but apply blob size estimation (ASMS) or apply key-point-like matching approaches (CMT, FoT, LGT). Average performance at moderate scale change is better for correlation filters than part-based trackers. Struck and MEEM are least affected by scale change among the trackers that do not adapt their scale. From the AR plots in Figure 5 it is apparent that the performance drops are due to a drop in accuracy, but not in failures.

Rotation: Rotation ($E_r$) significantly affects performance of all tracking classes. Figure 7 and the AR plots in Figure 5 show that the drop comes from a reduced accuracy as well as increased number of failures across most trackers. The drop is least apparent with ASMS, FoT and LGT which is likely due to their object visual models. The visual model in ASMS is rotation invariant since it is based on color histograms, while FoT and LGT explicitly address rotation by geometric matching. Rotation most significantly affects performance of correlation filters and ConvNets (Figure 6). These trackers apply templates for tracking and since rotation results in significant discrepancies between the template and object, the trackers fail. In particular, from the AR plots in Figures 5 we see that slow rotation ($E_r^s$) only results in decreased accuracy, but fast rotation ($E_r^f$) results in increased failures as well (e.g., SRDCF). On the
other hand, the performance of correlation filters, ConvNet tracker (SiamFC) and hybrid tracker (MEEM) surpasses the part-based models when no rotation is observed (E_b in Figures 5 and Figure 6).

**Motion:** From the AR plots in Figure 5, we see that slow planar motion (E_m^s) only slightly reduces performance in general, but this reduction is significant for most trackers in case of fast motion (E_m^f). LGT is the only tracker resilient to fast motion. A likely reason is the use of nearly-constant-velocity motion model in the LGT. However, the performance significantly drops for this tracker when extensive random motion is observed (E_m^r in Figure 6). Trackers like SiamFC and MEEM are least affected by all types of fast motions. The reason is likely in their very large search region for target localization. The AR plots in Figure 5 indicate that SiamCF fails much more often at fast motions (E_m^f) than MEEM implying that MEEM is more robust at local search.

**Object size:** All trackers perform very well in the baseline setup (E_b) in which the object is kept centered and of constant size (Figure 7 and Figure 6). In fact, top performance is achieved by the correlation filter trackers. The reason is that the visual model assumptions that these trackers make exactly fit this scenario. When considering smaller objects (E_b^s) the following trackers appear unaffected: ASMS, KCF, SRDCF, L1APG, CMT, FoT, LGT and MEEM. This implies that the level of detail of target representation in these trackers is unaffected by the reduced object size. Note that these trackers come from different classes. The AR plots in Figure 5 show that performance drop in tracking small objects is most significant for baselines like CT, IVT, MIL and Fragtrak as well as a sparse tracker ASLA and the Struck tracker. The performance drop comes from increased failures, which means that their representation is not discriminative enough on this scale which leads to frequent drifts.
Motion class difficulty: Considering the average EAO as fast movements and shaky videos, the weak spot of these trackers are target rotations, as well as the recent benchmarks, however, our analysis shows that the weak spot of these trackers are target rotations, as well as fast movements and shaky videos.

The OTB100 contains relative old trackers, therefore the intersection is in the following six trackers: ASLA, CT, FoT, IVT, L1-APG, MIL, and Struck. Figure 8 shows the ranking differences between these trackers for the different ranking modes. The ranking by average performance differs mainly L1-APG and FoT trackers. The possible reasons for this are different implementations, algorithm parameters, as well as different evaluation methodology. Three motion types in OTB100 are compatible with MoBe2016: scale variation, fast motion and in-plane rotation. Performance over three scale changing motion types on MoBe was averaged to obtain a scale change ranking. While the FoT achieves top performance on MoBe2016 it is positioned relatively low on OTB100, which is likely due to different implementations (ours is from the authors) and interaction of other attributes on OTB100. Both rankings place Struck at the top, ranks of other trackers vary. The fast motion ranking on MoBe2016 was obtained by averaging fast motions, i.e., $E_m^f$ and $E_m^w$. Both benchmarks rank Struck as top performing and IVT as worst performing. The in-plane rotation attribute was compared with combined ranking of center and displaced rotation ($E_r$ and $E_d$). The situation is similar to scale change, where FoT, which explicitly addresses rotation is ranked much lower according to OTB100.

Comparison with UAV123: The MoBe2016 and UAV123 intersect in the following seven trackers: ASLA, DSST, IVT, KCF, MEEM, SRDCF, and Struck. The comparison of average performance as well as with respect to three motion types scale variation, camera motion and fast motion is shown in Figure 8. The ranks are mostly consistent, the best two trackers are mostly SRDCF and MEEM. A discrepancy is observed for the MEEM tracker at scale change attribute. MEEM does not adapt the scale, which results in low rank at MoBe2016. But is ranked high on UAV123, which is likely due to attribute cross-talk. The discrepancy in KCF is due to implementation – our KCF adapts scale. Notice that the UAV123 ranks on camera motion are equal to scale variation ranks. We therefore compare both with ranks obtained by averaging fast in-plane motion ($E_m^f$) and large translation noise ($E_m^w$) performance on MoBe2016. The ranks match very well, which means that MoBe2016 offers a significant level of granularity in analysis.

6. Discussion and Conclusions

We have proposed a novel approach for single-target tracker evaluation on parameterized motion-related attributes. At the core of our approach is the use of 360 degree videos to generate annotated realistic-looking tracking scenarios. We have presented a novel benchmark MoBe2016, composed of annotated dataset of fifteen such videos and the results of 17 state-of-the-art trackers. The sequence generator, the 360 degree video annotation tools, the evaluation system and the benchmark will be made publicly available. The results of our experiment provide a detailed overview of strengths and limitations of modern short-term visual trackers.

As an example, the scale change appears to be well addressed by many tracking approaches. Even trackers that do not adapt scale do not fail often. Nevertheless, in practice
decrease greater than environment. The approach is complementary to existing benchmarks allowing better insights into tracking behavior on various motion types. Moreover, capturing 360 degree videos is nowadays possible with commodity equipment. Therefore our dataset adaptation to a specific tracking scenario may in fact be easier than in traditional approaches since it does not require careful planning before the acquisition to cover all possible motion types.

Our future work will focus on generalizing our framework to complex motion types and their effects on tracking performance. We also plan to explore adaptation of our evaluation methodology to active tracking.

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Table 2: Overview of the EAO scores and their relative differences according to the baseline EAO score of a tracker. The top value in each cell represents the absolute EAO score while the bottom one represents the EAO difference in relation to the baseline experiment. Green color denotes relative increase, orange color relative decrease, and red and bold red colors decrease greater than 25% and 50% of the baseline score. The baseline experiment is also not taken into account when computing average tracker score.
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