RGBD Object Tracking: An In-depth Review

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Abstract—RGBD object tracking is gaining momentum in computer vision research thanks to the development of depth sensors. Although numerous RGBD trackers have been proposed with promising performance, an in-depth review for comprehensive understanding of this area is lacking. In this paper, we firstly review RGBD object trackers from different perspectives, including RGBD fusion, depth usage, and tracking framework. Then, we summarize the existing datasets and the evaluation metrics. We benchmark a representative set of RGBD trackers, and give detailed analyses based on their performances. Particularly, we are the first to provide depth quality evaluation and analysis of tracking results in depth-friendly scenarios in RGBD tracking. For long-term settings in most RGBD tracking videos, we give an analysis of trackers’ performance on handling target disappearance. To enable better understanding of RGBD trackers, we propose robustness evaluation against input perturbations. Finally, we summarize the challenges and provide open directions for this community. All resources are publicly available at https://github.com/memoryunreal/RGBD-tracking-review.

Index Terms—RGBD tracking, Object tracking, RGBD fusion.

I. INTRODUCTION

Visual object tracking (VOT) aims at localizing an arbitrary object in a video sequence given the object description (center location and scale) in the first frame. Recent years have witnessed a great development of object tracking due to its diverse applications, e.g., autonomous driving [1], and robotics [2]. Problems like object occlusion, deformation, rotation, are still challenging in this field and have been extensively investigated by researchers. A large amount of RGB trackers, especially short-term trackers, emerge to boost this community. Since 2013, Kernelized Correlation Filter (KCF) [3] was introduced to solve the template matching problem. Due to the popularity of deep neural networks in computer vision, Siamese network and deep correlation filter based trackers are very popular in object tracking [4]–[10]. Progress in RGB tracking has been further boosted by the emergence of standard datasets and evaluation protocols. There are diverse and large datasets for model training and evaluation, such as OTB [11], GOT-10k [12] and TrackingNet [13]. This field is also fueled by the annual VOT challenges [14]–[19].

Although significant progress has been made in RGB-based tracking, there are still tracking failures that are hard to be solved by color information. Therefore, other modalities are added to provide complementary information, including depth, thermal, and event information [20]–[23]. Among them, RGBD (RGB + Depth) object tracking is gaining momentum in the past decade thanks to the affordable advanced depth cameras, such as Microsoft Kinect and Intel RealSense. On the one hand, depth maps provide essential cues on occlusion reasoning and depth-based object segmentation [24], [25]. For example, CA3DMS [26] uses a context-aware 3D mean-shift to handle occlusion, and DM-DCF [27] proposes a depth-based segmentation to train a constrained Discriminative Correlation Filter (DCF). On the other hand, RGBD channels can sense both appearance and geometric components for better object-and-background separation. For example, OTR [28] uses both color and depth information to build a spatial reliability map and reconstruct an object 3D model. Therefore, exploring the depth cue is indeed helpful for multi-modal tracking. Early RGBD trackers utilize direct heuristic extensions of RGB-based methods, which tend to extract hand-crafted features from depth maps to solve specific challenges. For example, PT [29] introduces a set of RGBD baseline trackers, including a traditional 2D tracker with additional depth HOG features, a 2D optical flow tracker, and a 3D point cloud tracker. Recently, deep networks are also introduced to RGBD tracking, but they are still straightforward extensions of RGB baselines [30]–[20]. At the same time, the annual VOT challenge [17] has had a specific track for RGBD input since 2019. By providing a test set and evaluation protocols, RGBD tracking can gain more attention in the object tracking community. Until now, there have been 13 participant RGBD trackers in the VOT-RGBD challenges [17]–[19]. According to VOT reports, the VOT trackers show superior performance over traditional solutions, and continuously improve the state-of-the-arts. A brief chronology of RGBD tracking is shown in Fig. 1.

As a newly developing area, research on RGBD tracking remains independent and non-systematic. There are many interesting topics required to be investigated as follows.

- How does depth information benefit tracking? According to conclusions from VOT-RGBD challenges, whether depth helps to track and what kind of methods are beneficial remains as an open question.
- How does depth data quality affect the tracking performance? The quality of depth maps is a vital issue, but its
impact on tracking has not been investigated before.

- What kinds of scenarios need help from depth information? Finding out the depth favorable scenarios can be meaningful for a wide range of applications in RGBD tracking and other related tasks.

- How does the long-term setting reflect on RGBD tracking? As RGBD tracking tends to be a long-term task, the effect of the target disappearance and reappearance requires to be investigated.

- How about the robustness of current tracking models? For RGBD tracking models, with inputs RGB and depth channels separately, a tiny perturbation on input can be of vital importance to tracking performance. However, how trackers perform with different input perturbations is an unexplored area.

This survey aims to provide a thorough review of this field and give in-depth analysis from various views. Our empirical analysis will answer the above questions and exploit the potential opportunity of using the depth components in tracking. Specifically, we restrict this survey to RGBD single object tracking. Some research areas are related but not covered here including multi-object tracking, RGB + Thermal tracking, 3D tracking as well as scene understanding [31, 32].

A. Related reviews and surveys

Table I lists several previous related reviews and surveys. Walia et al. [33] reviewed single-modal and multi-modal tracking methods preceding 2016. Camplani et al. [34] reviewed methods for tracking multiple humans with RGBD data. In 2016 and 2017, there were two surveys [35, 36] on existing RGBD datasets used in different applications, including object recognition, semantic reasoning and segmentation, human recognition, and pose estimation. Zhang et al. [37] focused on RGB and infrared tracking and outlined recent progress on RGBT tracking methods. Finally, a more recently published survey [38] covers both RGBT and RGBD tracking works until 2020.

Different from the above surveys, which focus on earlier datasets and algorithms, or related areas, this work systematically and comprehensively reviews RGBD object tracking from multiple perspectives. The rest of this paper is organized as follows. Sec. II summarizes existing RGBD tracking algorithms. Datasets and evaluation metrics are reviewed in Sec. III. Then, we conduct extensive experiments in Sec. IV, in which we compare overall performance (Sec. IV-A), examine the effect of depth data quality (Sec. IV-B), find out depth-related scenarios (Sec. IV-C), and give analysis on long-term setting (Sec. IV-D). Moreover, we evaluate robustness for RGBD trackers against input perturbations (Sec. IV-E). Finally, Sec. V gives in-depth discussions on future directions.

B. Contributions

Our contributions are:

- A systematic review of RGBD tracking models, datasets, and evaluation metrics. We categorize existing RGBD trackers from different perspectives, including fusion strategy, depth usage, and feature extraction. All existing RGBD object tracking benchmarks and evaluation metrics are reviewed as well.

- Performance evaluation of RGBD trackers. We compile a hybrid dataset and provide extensive experiments on 18 representative trackers, based on which we give detailed analysis to unfold the pros and cons of current RGBD datasets and trackers.

- An in-depth experimental analysis for RGBD object tracking from various aspects. We investigate several

| Table I: Summary of existing surveys in related fields. |
| --- | --- | --- | --- |
| Title | Scope | Year | Venue |
| Recent Advances on Multimodal Object Tracking: A Survey [8] | Multimodal object tracking | 2016 | AI Review |
| Multiple Human Tracking in RGB-D Data: A Survey [34] | RGBD multi-human tracking | 2016 | CVPR Vision |
| RGB-D Datasets Using Microsoft Kinect or Similar Sensors: A Survey [35] | RGBD dataset | 2017 | IMA |
| Object Fusion Tracking Based on Visible and Infrared Images: A Comprehensive Review [37] | RGBT object tracking | 2020 | Submitted to PR |
| Multi-modal Visual Tracking: Review and Experimental Comparison [38] | Multimodal object tracking | 2020 | Submitted to PR |

Fig. 1: Chronology of RGBD object tracking.
TABLE II: Statistics of RGBD tracking models. “CL/DL” indicates whether the tracker is a classical/deep-learning based method. “ST/LT” indicates short-term/long-term trackers. “Occ.Han.” indicates occlusion handling.

| Method                | Year | Publication | CL/DL | Framework | Backbone | Training data | ST/LT | Occ.Han. | Code |
|-----------------------|------|-------------|-------|-----------|----------|---------------|-------|----------|------|
| ASOS [59]             | 2012 | ICCV        | CL    | Condensation | -       | -             | ST    |          |      |
| PT [29]               | 2013 | CVPR        | CL    | SVM       | -        | -             | LT    |          |      |
| MCBT [40]             | 2014 | Neurocomputing | CL | KCF     | -        | -             | LT    |          |      |
| DS-KCF [41]           | 2015 | BMVC        | CL    | SURF      | -        | ST            |       |          |      |
| OL3DC [52]            | 2015 | Neurocomputing | CL | CAC      | -        | -             | LT    |          |      |
| CDO [43]              | 2015 | CVPR        | CL    | SVM       | -        | -             | LT    |          |      |
| DOHR [44]             | 2015 | FSDK        | CL    | Bayesian  | -        | -             | LT    |          |      |
| DSOID [45]            | 2015 | Signal Processing | CL | KCF     | -        | -             | LT    |          |      |
| DS-KCF, shape [46]    | 2016 | JRTIP       | CL    | KCF      | -        | ST            |       |          |      |
| 3D-T [47]             | 2016 | CVPR        | CL    | KCF      | -        | LT            |       |          |      |
| OAPF [48]             | 2016 | CVIU        | CL    | Particle Filter | -   | -             | LT    |          |      |
| DLS [49]              | 2016 | ICPR        | CL    | KCF      | -        | LT            |       |          |      |
| ODIFT [50]            | 2017 | Neural Processing Letters | CL | TLD  | -        | -             | LT    |          |      |
| ROTS [51]             | 2017 | ITEE        | CL    | Particle filter | -   | -             | LT    |          |      |
| CSR_RGBD++ [53]       | 2018 | IEEE TCCYB  | CL    | KCF      | -        | ST            |       |          |      |
| DS-KCF [41]           | 2018 | ECCVW       | CL    | CSR_DCF  | -        | -             | LT    |          |      |
| DM-DCF [27]           | 2018 | ICCP        | CL    | CSR_DCF  | -        | -             | ST    |          |      |
| OAPF [48]             | 2018 | IEEE Sensors | CL | KCF      | -        | -             | LT    |          |      |
| OAPF [48]             | 2018 | IEEE Sensors | CL | Particle filter | -   | -             | LT    |          |      |
| OAPF [48]             | 2018 | IEEE Sensors | CL | KCF      | -        | -             | LT    |          |      |
| OAPF [48]             | 2018 | IEEE Sensors | CL | KCF      | -        | -             | LT    |          |      |
| ORG [54]              | 2019 | CVPR        | CL    | CSR_DCF  | -        | -             | LT    |          |      |
| Depth-CCF [55]        | 2019 | IOP         | CL    | DCF      | -        | -             | LT    |          |      |
| ECO_TA [58]           | 2019 | IEEE Sensors | CL | ECO      | -        | -             | ST    |          |      |
| RGBD-OD [59]          | 2019 | CIS         | CL    | PointNet | -        | Point pre-trained |       |          |      |
| H-FCN [60]            | 2019 | Information Fusion | CL | ECO   | -        | -             | LT    |          |      |
| 3DS [61]              | 2019 | ICST        | CL    | Mean Shift | -   | -             | LT    |          |      |
| WCO [62]              | 2020 | IEEE Sensors | CL | DCF      | -        | ST            |       |          |      |
| RF-CFF [63]           | 2020 | Applied Soft Computing | DL | SiamDW-RPN | ResNet-18 | RGB pre-trained | LT    |          |      |
| SiamOC [64]           | 2020 | ICSP        | DL    | SiamDW-RPN | ResNet-18 | RGB pre-trained | LT    |          |      |
| DAL [65]              | 2020 | ICPR        | DL    | SiamDW-RPN | ResNet-18 | RGB pre-trained | ST    |          |      |
| 3s-RGBD [66]          | 2021 | Neurocomputing | DL | SiamFC  | AlexNet  | RGB pre-trained | LT    |          |      |
| TSDM [67]             | 2021 | ICPR        | DL    | SiamRPN++ | ResNet-50 | RGB pre-trained | ST    |          |      |
| DS-3 [68]             | 2021 | ICPR        | DL    | SiamRPN+ | ResNet-50 | RGB pre-trained | ST    |          |      |
| ATCAI19 [70]          | 2019 | VOT-2019   | DL    | SiamDW  | ResNet-50 | RGB pre-trained | LT    |          |      |
| SiamDW_D              | 2019 | VOT-2019   | DL    | SiamMask | ResNet-50 | RGB pre-trained | ST    |          |      |
| SiamM_Ds              | 2019 | VOT-2019   | DL    | SiamMask | ResNet-50 | RGB pre-trained | ST    |          |      |
| LTDSEd                | 2019 | VOT-2019   | DL    | LT-DSE   | ResNet-50 | RGB pre-trained | ST    |          |      |
| ATCAI20 [70]          | 2020 | VOT-2020   | DL    | ATOM     | ResNet-18 | RGB pre-trained | LT    |          |      |
| CLGS_D                | 2020 | VOT-2020   | DL    | ATOM     | ResNet-18 | RGB pre-trained | LT    |          |      |
| DDiMP                 | 2020 | VOT-2020   | DL    | SiamMask | ResNet-50 | RGB pre-trained | ST    |          |      |
| Siam_LTD              | 2020 | VOT-2020   | DL    | SiamRPN  | ResNet-50 | RGB pre-trained | ST    |          |      |
| SiamRPN++             | 2020 | VOT-2021   | DL    | STARK    | ResNet-50 | RGB pre-trained | ST    |          |      |
| STARK_RGBD            | 2021 | VOT-2021   | DL    | STARK    | ResNet-50 | RGB pre-trained | ST    |          |      |
| SLM [71]              | 2021 | VOT-2021   | DL    | PrDiMP   | ResNet-50 | RGB pre-trained | LT    |          |      |
| TALGD [72]            | 2021 | VOT-2021   | DL    | SuperDiMP | ResNet-50 | RGB pre-trained | LT    |          |      |
| DRefine              | 2021 | VOT-2021   | DL    | SuperDiMP | ResNet-50 | RGB pre-trained | ST    |          |      |

Important components, including the effect of depth data quality, attribute-based analysis, and long-term setting effects. In particular, we are the first to study robustness to input perturbations in RGBD object tracking.

- **Overview of challenges and open directions.** From our empirical analysis of RGBD object tracking, we thoroughly investigate the challenges for RGBD tracking and provide potential directions for future research.

II. MODELS AND TAXONOMY

To systematically review RGBD trackers, we categorize the models. There are mainly three taxonomies: RGB and depth fusion paradigm, depth usage, and feature extraction method. We specifically focus on the trackers participants in VOT RGBD tracking challenges. In the following, several representative models in each taxonomy will be described. Table II summarizes existing RGBD trackers.

A. Early/late RGBD fusion

Existing fusion strategies in RGBD tracking can be divided into early fusion and late fusion.

1) Early fusion: Early fusion based models generally follow two strategies: RGB and depth images are first fed into independent feature extraction modules separately and then combined. Then the combined feature map is used to obtain a final prediction, such as DS-KCF [41], CSR_RGBD++ [27], ECO_TA [58]. Another strategy is to integrate the depth channel with RGB channels to form a four-channel input, such as PT [29]. For early fusion, MCBT [40] combines optical flow, color, and depth information, which are simultaneously incorporated to predict the precise position. Camplani et al. proposed DS-KCF [41] which utilized HoG features for both color and depth maps. OAPF [48] employs multiple features, e.g. HoG, from color and depth streams to improve robustness.
against illumination changes and clutter and boost the performance. Another example is DeT [20], which extracts depth features by using an additional depth branch. With fusing the color feature and depth feature, it can use ATOM [5] or DiMP [7] tail part to perform the actual tracking.

2) Late fusion: Late fusion based models generally process both modalities simultaneously, and the independent models for RGB stream and depth stream are built to make decisions. For example, Xiao et al. proposed STC [52] which fuses two single-modal trackers through weighted maps. CDG [43] uses depth gradient information to extract depth motion models and weights the results from RGB and depth models. RT-KCF [40] fuses response maps instead of features to get a good performance. RF-CFF [63] focuses on fusing tracking results of RGB and depth images, in which objects are tracked in RGB and depth images separately using the correlation filter. Then results from RGB and depth images are adaptively fused.

B. 2D/3D depth usage

Since depth maps provide appearance descriptions and geometry information for tracked objects, there are some methods treating depth maps in 2D and 3D structures, respectively.

1) 2D usage: Depth map naturally provides a texture-free segmentation between foreground and background, so it is common to use depth cues for object segmentation. In CSR_RGBD++, [53], a depth augmented foreground segmentation is formulated by graph cut to obtain a foreground mask in the target update. DM-DCF [27] extracts the depth-based segmentation masks in order to train a constrained DCF.

2) 3D usage: Depth information provides the 3D spatial description of objects. Representative trackers include OTR [28], CA3DMS [26] and 3D-T [47]. Among them, 3D-T [47] is the first 3D part-based tracker, which exploits parts to preserve temporal structural information and helps in particle pruning. CA3DMS [26] is a 3D extension of the classical mean-shift tracker, aiming to address two shortboards of 3D mean-shift: the online adaption and total occlusion handling. OTR [28] implements online 3D object construction to learn a robust view-specific discriminative correlation filter (DCF), extending the 2D tracking structure to 3D representation. The 3D construction benefits the tracking performance from two aspects: generation of spatial description for the constrained 2D DCF learning; 3D pose estimation based on point clouds to localize the object after heavy occlusion.

3) Mixed usage: There are also hybrid trackers which jointly use 2D and 3D models to combine 2D appearance features and 3D spatial features. For example, DLS [49] simultaneously builds two target models: a 2D appearance model built upon the features extracted from both color and depth frames, and a 3D distribution model built according to the point cloud distribution on the target surface. The depth histogram is used to adaptively segment the target in depth frames and project cloud points into a depth image patch. SEOH [54] employs the spatial continuity in depth values for scale estimation, and a part-based model updating strategy to deal with occlusion. Another representative is TSDM [30], consisting of an RGB tracking core and two assistant modules. First, the core is SiamRPN++ [10], which takes an image pair (template and mask images) as input. Then, a mask-generator module utilizes depth information to generate a mask image for a candidate search image. Finally, a depth-refiner module cuts out non-target areas from the original outputs and gives a smaller and more precise mask.

C. Heuristic/deep models

Depth information provides useful cues, e.g. boundary cues, and helps to identify object characteristics. Over the past several years, many traditional trackers with handcrafted features are designed by using these specific cues. For example, MCBT [40] uses the depth mean and variance in the target region to measure the difference between candidates and templates. PT [29] proposes a series of baseline trackers with handcrafted features, including a traditional 2D image patch-based tracker, a 3D point cloud-based tracker, and a low-level optical flow-based tracker. STC [52] first uses depth HOG as depth features, and then the RGB and depth features are separately used in KCF to find the target position in a global layer. As shown in Table II, there are many methods specially designed for occlusion handling since depth cues straightforward indicate the target locations. ISOD [45] exploits depth information obtained from binocular video data to detect occlusion, which prevents improper appearance model updating during occlusions. Meshgi et al. [48] proposed an occlusion aware particle filter framework that employs a probabilistic model with a latent variable to represent an occlusion flag. Liu et al. [20] proposed a context-aware 3D Meanshift method, which compares depth differences between the target and the occluder, and between the nearby 3D point and the occluder to detect and recover from tracking failures caused by full occlusions. CSR_RGBD++ [53] sets multiple assumptions in the occlusion recovery stage (the positions are similar before disappearing and after disappearing, the target speed remains constant) to recapture the object.

However, due to the limited-expression ability of handcrafted features, deep neural networks are introduced to RGBD tracking. Generally, deep learning-based models follow two principles: 1) Trackers integrate RGB features extracted by pre-trained deep neural networks with handcrafted depth features into heuristic tracking frameworks [30], [65]. 2) Trackers are trained on both RGB and depth data jointly to obtain deep depth features as well as deep RGB features. However, up to now, almost all trackers follow the first principle and remain on using the deep features extracted by pre-trained models on RGB datasets. Some representative models are briefly introduced here. In addition to the Siamese tracking network, SiamOC [64] provides two modules to consider both depth histogram characteristics and movement smoothness, simultaneously. The underlying assumption is that different objects have different depth histogram characteristics. DAL [65] embeds depth information into deep features through the formulation of a deep discriminative correlation filter (DCF). TSDM [30] equips SiamRPN++ [10] with two assistant depth-related modules. Until 2021, the trainable RGBD tracker DeT [20] is first proposed with duplicating a separate feature extraction branch for depth colormaps.
D. VOT participants

Since 2019, there have been 3 VOT-RGBD challenges [17]–[19] held annually, consisting of 13 participating trackers in total. Most participants in VOT just provide a tracking model and brief introduction without specific publications yet they show outstanding performance in multi-challenges. Therefore, we here review representative VOT participants as well.

2019 Winner: SiamDW-D is a long-term tracker which addresses the problems of target appearance variations and frequent target loss. It contains three parts, i.e., the main tracker, a re-detection module, and a multi-template matching module. The main tracker is based on [6], and further equips with an online updating model [5], [67]. The re-detection module is triggered when the main tracker is not confident in its predictions. The multi-template matching module is to output a more reliable estimation when the tracking results are unreliable with history templates. Moreover, depth information is used to estimate the disappearance of target objects.

2020 Winner: ATCAIS combines both instance segmentation and depth information for accurate tracking. It is based on ATOM [5] and the HTC instance segmentation method [68], which is retrained in a category-agnostic manner. The instance segmentation results are used to detect background distractors and to refine the target bounding boxes to prevent drifting. The depth value is used to detect the target occlusion or disappearance and redetect the target.

2021 Winner: STARK_RGBD is a method combining STARK [69] and DiMPsuper [7]. Here STRAK variant DeiT [70] is used to strengthen the features of STARK. To better handle the appearance change of the target, DeiT combines with the DiMPsuper model. Specifically, when the STARK tracker’s confidence is low or the prediction of STARK suddenly strays away, DiMPsuper takes over the tracking process, providing an appearance adaptive result. In addition, a refinement module based on AlphaRefine [71] is applied to the final output of the whole tracking system for further boosting the quality of box estimation.

Besides the annual winners, other participants also give solutions on RGBD tracking. In DDIMP [18], depth information is utilized to prevent scale from changing too quickly. As targets cannot have very large displacements in two consecutive frames, SiamM_Ds [17] averages the depth from the depth image inside the object candidate to determine the depth of the target as a constraint. TALGD [19] uses depth images for occlusion or disappearance reasoning and target retrieval. CLGS-D [17] uses depth maps to filter region proposals. Note that some participants do not use depth information indeed, including sttc_rgbd, DRefine, and STARK_RGBD, while they still keep high performance.

III. DATASETS AND EVALUATION METRICS

A. Datasets

In RGBD tracking, early datasets only contain a few sequences for evaluation. In 2012, a small-scale dataset called BoBoT-D [39] was proposed, consisting of five RGBD video sequences captured by Microsoft Kinect v1.0. In [40], four videos were captured and utilized for evaluation with four kinds of objects (Book, Face, Inno, and TeaCan). These video sequences represent different challenges, such as occlusion, rotation, illumination change, shape variation of a flexible object, and small target, and are manually annotated the groundtruth every five frames.

From 2013, benchmark datasets have appeared for wide use. Up to now, there are four datasets dedicated designed and widely used for RGBD object tracking. The Table VIII compares the four representative RGBD tracking datasets. Fig. 2 gives chronology and examples of these datasets. The details of each dataset are given as follows:

Princeton Tracking Benchmark (PTB) [29]. As the first dataset designed for RGBD object tracking, PTB contains 100 RGBD video clips recorded by Microsoft Kinect v1.0. There are only 3 types: human, animal, and rigid object, with more than half of the sequences, are for people tracking. For a fair comparison, PTB withholds groundtruth for 95 videos and hosts an online evaluation server to allow new result submissions. The remaining 5 videos are public for tracker validation before submitting their results. It is worth noting that the RGB and depth channels are poorly calibrated in PTB. In approximately 14% of sequences, the RGB and D channels are not synchronized and approximately 8% are miss-aligned, which was fixed by [47].

Spatial-Temporal Consistency Dataset (STC) [52]. It was proposed in 2018 to address the drawbacks of the PTB dataset. It is designed to increase the data diversity with a compact size of only 36 sequences for short-term RGBD tracker evaluation. STC dataset constrains the dataset mostly to indoor scenarios and there are only a few low-light outdoor video clips. Although the STC dataset is the smallest dataset among the RGBD tracking family, it is annotated with 13 attributes and uses two kinds of evaluation metrics imported from OTB [11] and VOT protocols [14].

Color-and-Depth Tracking Benchmark (CDTB) [72]. It includes 80 video sequences for long-term tracking with an average video length of 1274 frames. With long-term settings, objects are possibly fully occluded or out-of-view for a long duration and thus, it can be used to evaluate the re-detection performance. Note that the CDTB is the only dataset acquired by multiple color-and-depth sensors, which guarantees its diversity of realistic depth signals. Indoor, as well as outdoor scenarios, are covered to extend the tracking domains.

DepthTrack Dataset [20]. It consists of 200 sequences, which is the currently largest and most diverse dataset for RGBD tracking. Specifically, it includes the most diverse object types (46 categories in 50 test sequences), scenarios (indoors and outdoors with 15 attributes), and video length (varying from 143 to 3816 frames). Until now, it is the first and the only RGBD tracking dataset divided into training and test sets. In addition, with long-term tracking settings, the DepthTrack dataset is dedicated to exploring the depth-related power to assist in tracking challenges.

B. Evaluation metrics

Although there are only four datasets, their evaluation protocols are different. In this section, we give representative
evaluation metrics for RGBD object tracking in detail, i.e., Success Rate (SR), Pr-Re (Precision-Recall), and F-score.

**Success Rate (SR).** Inspired by PASCAL VOC challenge\[73\], for \(t\)-th frame, the overlap ratio \(r_t\) between the predicted bounding box \(A_t\) and the groundtruth bounding box \(G_t\) is:

\[
r_t = \begin{cases} \frac{\text{area}(A_t \cap G_t)}{\text{area}(A_t \cup G_t)} & \text{both } A_t \text{ and } G_t \text{ exist} \\ 1 & \text{neither } A_t \text{ or } G_t \text{ exists} \\ -1 & \text{otherwise} \end{cases}
\]

Then, a minimum overlapping area ratio \(r\) can be used to decide whether the output is correct. Thus, the average success rate \(R\) of each tracker is defined as follows:

\[
R = \frac{1}{N} \sum_{t=1}^{N} u_t, \quad \text{where } u_t = \begin{cases} 1 \text{ if } r_t > r \\ 0 \text{ otherwise} \end{cases}
\]

where \(u_t\) denotes whether the output bounding box of the \(t\)-th frame is acceptable, and \(N\) is the number of frames.

**Precision-Recall (Pr-Re) & F-score.** According to the settings of the VOT challenges\[17\][18\], the most popular metric in RGBD tracking is the precision-recall and F-score\[74\]. As the video length over different datasets and sequences varies dramatically, there are frame-based and sequence-based evaluation protocols. At frame \(t\), \(\theta_t\) is a prediction confidence score and \(\tau_0\) is a classification threshold. If the predicted confidence score \(\theta_t\) is not below \(\tau_0\), \(A_t(\tau_0)\) is used to denote the corresponding prediction. Otherwise, the output is an empty set and we set \(A_t(\tau_0) = \emptyset\). Thus, \(\Omega(A_t(\tau_0), G_t)\) can be used to indicate the intersection-over-union (IoU) between the prediction result \(A_t(\tau_0)\) and the groundtruth \(G_t\). Then, the frame-based evaluation is as follows:

\[
Pr(\tau_0) = \frac{1}{N_p} \sum_{i \in N_p} \Omega(A_t(\tau_0), G_t), \\
Re(\tau_0) = \frac{1}{N_g} \sum_{i \in N_g} \Omega(A_t(\tau_0), G_t), \tag{3}
\]

\[
F(\tau_0) = \frac{2Pr(\tau_0)Re(\tau_0)}{Pr(\tau_0) + Re(\tau_0)}
\]

where \(F(\tau_0)\), \(Pr(\tau_0)\) and \(Re(\tau_0)\) denote the F-score metric, the precision (Pr) and the recall (Re) over all frames, respectively. \(N_p\) denotes the number of frames in which the target is predicted visible, and \(N_g\) denotes the number of frames in which the target is indeed visible.

For sequence-based evaluation, the precision-recall over all sequences is as follows:

\[
Pr^i(\tau_0) = \frac{1}{M} \sum_{i=1}^{M} Pr^i(\tau_0), \\
Re^i(\tau_0) = \frac{1}{M} \sum_{i=1}^{M} Re^i(\tau_0), \tag{4}
\]

where \(Pr^i(\tau_0)\) and \(Re^i(\tau_0)\) denote the precision and recall metrics for \(i\)-th sequence among \(M\) test videos. F-score is obtained in the same way as Eq. 3.

\section{C. Annotation and Attribute}

All datasets are given with per-frame axis-aligned bounding box annotation. Fig. 5 illustrates the bounding box distributions for STC, CDTB, and DepthTrack datasets. Due to its privacy of test data groundtruth, the PTB dataset is not included. As shown, there are high discrepancies between bounding box distributions of different datasets.

In the field of object tracking, “attribute” defines possible challenging factors and different characteristics of each.
sequence. Existing datasets propose various attributes from various perspectives. 1) PTB dataset evaluates trackers on target type (human/animal/rigid), target size (large/small), movement (slow/fast), occlusion (yes/no), and motion type (active/passive). 2) STC dataset annotates the attributes per sequence, including Illumination Variation (IV), Color/Depth Distribution Variation (CDV/DDV), Surrounding Depth/Color Clutter (SDC/SCC), Background Color/Shape Camouflages (BCC/BSC), Partial Occlusion (PO), and Depth/Scale Variation (DV/SV). 3) CDTB and DepthTrack datasets share the most attributes, including the common challenges that appeared in RGB-based tracking: Aspect Change (AC), Fast Motion (FM), Full Occlusion (FO), Non-rigid Deformation (ND), Out-of-plane Rotation (OP), Out-of-frame (OF), Partial Occlusion (PO), Size Change (SC), and Similar Objects (SO), and depth-related challenges: Dark Scene (DS), Depth Change (DC), and Reflective Targets (RT). 4) In particular, the DepthTrack dataset considers two more challenges, such as Background Clutter (BC) and Camera Motion (CM) which are indirectly related to depth scenarios.

### IV. Benchmarking and Empirical Analysis

To give empirical analysis on the key challenges in RGBD tracking, we specifically conduct a series of studies to better understand the benefits and deficiencies of current arts. To this end, we first collect the public RGBD tracking data to make a unified benchmark, and then, the experiments conducted on it can uncover meaningful findings on current arts. Specifically, we propose a depth data quality study to investigate its effect on tracking performance (Sec. IV-B). Secondly, we explore depth favorable scenarios which significantly affect the role of depth cues in the tracking process (Sec. IV-C). Then, we analyze the effect of long-term components and compare the speed over various RGBD trackers. Finally, we quantitatively evaluate the tracking robustness of RGBD trackers against input perturbations (Sec. IV-E).

#### A. Benchmarking performance

For benchmarking performance on different datasets, we conduct a hybrid dataset for in-depth analysis. We collect the public RGBD tracking test data for evaluation from the aforementioned STC [52], CDTB [72], and DepthTrack [20] datasets. Thus, the hybrid dataset contains 166 video sequences, with 187,514 frames. For a unified comparison, we use a frame-based F-score (see Eq. 3) as the evaluation protocol. All the benchmark trackers are representative and have officially available implementations. All results are obtained by running with their official codes. It is worth noting that some early trackers are not able to report confidence scores so we set the confidence score as 1 for every frame.

Overall performance is given in Table II and Fig. 4. Obviously, data-driven models greatly outperform conventional heuristic ones. Traditional methods perform poorly on current larger and more challenging datasets. From 2015 to 2018, the development of RGBD trackers was slow. In fact, the VOT RGBD competition which was first held in 2019, started to promote the research of RGBD trackers into the field of deep models. Specifically, VOT participants mostly outperform on F-score, showing high generalization ability and tracking performance. But their speeds are relatively low, far below the real-time requirement. Here we also report the speed-performance trade-off in Fig. 5 which has not been included and analyzed in most related works. As shown, DeT [20] achieves the best on speed-performance trade-off. However, many high-performance RGBD trackers are sub-optimal, indicating they may sacrifice tracking speed for the sake of tracking accuracy.

#### B. Effect of depth data quality

Since depth images provide very important complementary information for object tracking, their quality is very important. Due to the limitations of depth sensors, the poor depth quality contains challenges including asynchrony between color and depth channels, low resolution, median and Gaussian blur, and color distortion. To investigate how depth data quality affects tracking performance, we divide the RGBD video sequences into three groups (low quality, medium quality, and high quality) according to their depth quality level for performance comparison. Hence, we evaluate the Depth Quality (DQ) based on the Bad Point Rate (BPR) proposed in [75], in which $DQ = 1 - BPR$. BPR is a state-of-the-art no-reference depth assessment metric and matches the texture edges and depth edges to measure the proportion of mismatched pixels. The lower BPR value denotes the better depth quality.
Fig. 4: Overall performance of RGBD trackers on the hybrid dataset.

When evaluating the depth quality of STC, CDTB, and DepthTrack datasets, we calculate the depth quality of the three datasets to be 0.2450, 0.7012, and 0.4901, respectively. Among them, the depth quality of the CDTB dataset is the worst. By visualizing the depth map, as shown in Fig. 7, we find that the resolution of depth images does not match the ones of color images in the CDTB dataset, resulting in lots of empty depth values after aligning the depth image to the color image. To effectively investigate the quality impact of depth maps, we conduct the experiments by removing these sequences from the CDTB dataset. The results show that the quality of depth maps has relatively little impact on their performance. The inherent reason is that most deep models heavily depend on the pre-trained RGB tracking models. With only heuristic depth features used on specific occasions, e.g., occlusion detection, the depth quality does not affect the final performance so much. Among all these methods, DeT conversely shows 0.80% higher performance on medium-quality datasets relative to high-quality datasets. It can be seen that the quality of DepthTrack dataset is generally low. It is due to that DeT is trained on the DepthTrack training set, indicating there may be domain overfitting on DepthTrack.

C. Attribute-based analysis

In RGBD tracking, numerous factors affect the tracker performance. To investigate how trackers benefit from specific components, we evaluate trackers’ performance under different scenarios. This helps to reveal the strength of RGBD trackers and find out the scenarios that which depth cues can...
benefit. Moreover, depth favorable scenarios are essential for researchers to bridge the gap between 2D and 3D tracking, which are surprisingly unexplored in RGBD tracking. We select and classify the depth-related issues from existing RGBD tracking datasets. The depth-related scenarios tags include Depth Change (DC), Reflective Target (RT), Dark Scenes (DS), Background Clutter (BC), Similar Objects (SO). We specifically evaluate the tracker performance within these attributes. STARK_RGBD [19] performs best on correlated frames with all listed types of attributes, which demonstrates its effectiveness. As we reviewed in Sec. II STARK_RGBD does not use depth information indeed, while it leads the leaderboard of many RGB tracking benchmarks. Thus, the tracking performance highly relies on the pre-trained trackers’ discriminative ability. Despite this, dark scenes and depth change are well handled by TALGD [19] by using depth maps for reasoning target disappearance and retrieval. DeT [20] shows good performance on background clutter, due to its depth deep features which can distinguish the objects from background distractors in depth colormaps. In addition, DDIMP [18] and sttc_rgbd [19] are good at reflective targets and similar objects, respectively. Overall, background clutter and similar objects are especially challenging for RGBD trackers with the highest F-scores of 0.519 and 0.493, respectively.

### D. Long-term analysis

Long-term tracking is gaining more attention because it is much closer to practical applications than short-term tracking. In visual object tracking, long-term tracking is defined as: the object can temporally disappear, due to occlusion or out-of-view, and re-appear in one video sequence. In RGBD tracking, such difficulties due to the long-term settings (targets are fully occluded or out-of-view) are more common. As shown in Table II many RGBD trackers are designed for occlusion handling. Therefore, we evaluate how state-of-the-art trackers handle the target loss and reappearance. For evaluation, 66 sequences (98558 frames) with target loss (occlusion or out-of-view) are selected from our hybrid dataset. The qualitative results are shown in Table VII. Generally, tracking perf-
Table VII: Long-term component analysis. “Drop” denotes the performance drop after target loss. Short-term trackers are shown in red, and heuristic methods are shown in brown.

| Method          | LT/ST | Before Occ | After Occ | Drop  |
|-----------------|-------|------------|-----------|-------|
| DeT [20]        | ST    | 0.731      | 0.341     | 0.390 |
| CA3DMS [26]     | LT    | 0.444      | 0.090     | 0.354 |
| CSR_RGBD++ [53] | LT    | 0.320      | 0.028     | 0.292 |
| Siam_LTD [18]   | LT    | 0.544      | 0.315     | 0.229 |
| ATCAIS [17]     | LT    | 0.653      | 0.457     | 0.196 |
| DRefine [19]    | ST    | 0.646      | 0.456     | 0.190 |
| TSDM [30]       | LT    | 0.530      | 0.351     | 0.179 |
| SiamDWD [17]    | LT    | 0.496      | 0.318     | 0.178 |
| stc_rbgd [17]   | ST    | 0.655      | 0.483     | 0.172 |
| CLGS-D [15]     | LT    | 0.641      | 0.470     | 0.171 |
| DDiMP [18]      | ST    | 0.650      | 0.483     | 0.167 |
| STARK_RGBD [19] | LT    | 0.716      | 0.552     | 0.164 |
| DAL [43]        | LT    | 0.573      | 0.410     | 0.163 |
| SLMD [19]       | LT    | 0.640      | 0.483     | 0.157 |
| TALGD [19]      | LT    | 0.666      | 0.544     | 0.122 |
| LTDSeD [17]     | LT    | 0.446      | 0.368     | 0.078 |

The task of object tracking can be viewed as a self-supervised learning problem due to the solely bounding box input. Since trackers can be very sensitive to the input bounding box, tracking robustness against the input perturbations is an essential issue to judge the performance of a tracker. However, RGBD tracking methods are compared merely using a one-pass evaluation metric for a long time. To further investigate the performance, in this section, we propose to evaluate the robustness by comparing their performance against different perturbed inputs, such as rotation and scale, and different initialization frames. We choose four SOTA deep models, i.e., TSDM [30], DAL [65], DeT [20], STARK_RGBD [19], and two heuristic models, i.e., CSR_RGBD++ [27] and DS_KCF_shape [46]. The detailed experimental comparison is as follows.
TABLE VIII: Robustness evaluation with input perturbations on the hybrid benchmark. “Change” denotes the performance change compared to the original F-score.

| Method      | SRE F-Score/Change | TRE F-Score/Change | RTRE F-Score/Change |
|-------------|-------------------|-------------------|---------------------|
| DeT [20]    | 0.321/-0.035      | 0.357/-0.018      | 0.449/-0.077        |
| DAL         | 0.484/-0.042      | 0.544/-0.018      | 0.449/-0.077        |
| TSDM [30]   | 0.432/-0.040      | 0.474/-0.002      | 0.323/-0.149        |
| STARK_RGBD [19] | 0.606/-0.051   | 0.667/-0.010      | 0.580/-0.077        |
| CSR_RGBD++ [27] | 0.148/-0.015   | 0.166/-0.003      | 0.100/-0.063        |
| DS_KCF_shape [46] | 0.035/-0.005   | 0.0396/-0.0001    | 0.0292/-0.0105      |
| Average     | 0.3095/-0.0334    | 0.3414/-0.0085    | 0.3230/-0.0799      |

1) Spatial robustness evaluation (SRE): In applications, the target is generally initialized manually, and thus some annotation noises will be introduced. Thus, we usually require trackers to be stable relative to such noises. To test the spatial robustness, we simulate the annotation error by slightly shifting or scaling the initialization state of the target. We here use eight spatial shifts and four scale variations. For the spatial shifts, we set the spatial shift as 10% of target width, length, and corners (right, left, top, bottom shift by 10%, and four corners shift by 10%). The amount for the scale variation is 10% of the target size, and the scale ratio varies from 80% to 120%. The SRE score for a tracker is the average of these 12 evaluations. As shown in Table VIII, the average F-score change in SRE is -0.0334, indicating that spatial perturbations can prevent the trackers from reliable predictions.

2) Temporal robustness evaluation (TRE): Each tracking algorithm is evaluated multiple times by setting the initial bounding box in different frames of the video sequence. In each evaluation, the tracking algorithm starts from a specific initial frame, obtains the corresponding annotated target state, then predicts subsequent frames of the video sequence until the end of the sequence. The average of all the test results will be taken as the TRE score of the tested algorithm. As shown in Table VIII, the average F-score change in TRE is +0.0085 in the TRE, which indicates TRE has tiny effects on tracker robustness. For SRE, the initialized target state is offset from the ground truth bounding boxes, whereas for TRE the initialized target state is still obtained from the ground truth bounding boxes. Thus, the start frame changes do not affect the models very heavily. Moreover, almost all F-scores improve slightly due to video length shortening. Another reason is that researchers naturally tend to show the whole object characteristics in the very beginning since the data is collected manually, leading to the phenomenon that the tracking difficulty goes higher with video playing.

3) Reverse temporal robustness evaluation (RTRE): From observing the RGBD video characteristics, we propose RTRE which evaluates the tracker robustness with video streams in the reverse direction. As shown in Table VIII F-scores drop severely with an average of 0.0799 due to the reverse operation of RGBD videos, indicating the test videos are more challenging in reverse order. Overall, STARK_RGBD [19] is the most robust, while DeT [20] and TSDM [30] drop most heavily on F-score. Overall, deep tracking models [19], [20], [30], [65] are more sensitive than the traditional ones [27], [46]. The gap between TRE and RTRE indicates that there exists data bias in current RGBD video sequences, which can be alleviated in future dataset design.

V. DISCUSSIONS

A. Dataset construction

1) High-quality dataset: Based on the experiments in Sec. IV-B, we conclude that low depth quality has side effects on tracking performance. To develop RGBD object tracking, collecting high-quality data resources is very important. Due to the limitations of depth sensors, the collection range of depth maps is lower than 10m, in which we can only get precise depth maps between 0.5m-6m. Thus, the pre-processing of low-quality depth videos is also an important step. In addition, the synchronization and registration noise also damages tracking performance as well. Thus, both reliable depth information and correctly synchronized RGBD data are necessary for trackers to effectively combine the multi-modal information.

2) Domain-specific dataset: Due to different application scenarios, there are datasets specifically designed for different applications, e.g., UAV tracking, small-sized object tracking, etc. However, there are no such datasets for RGBD tracking. As RGBD tracking has shown potential on a wide range of applications, collecting such domain-specific datasets may benefit the application of it on specific scenarios, e.g., nighttime scenarios and UAV tracking scenarios.

3) Data annotation: Advanced RGB-based tracking benchmarks are transferred to more accurate and fine-grained annotation with mask annotations, while RGBD benchmark datasets remain on axis-aligned bounding boxes. The bounding boxes prevent RGBD trackers from better describing the object, especially the irregularly shaped and deformable objects. A potential direction of RGBD tracking is to develop pixel-level RGBD tracking algorithms, which indeed need more precise data annotations.

4) Challenging videos: Compared with the RGB dataset, which can be randomly intercepted from the Internet, RGBD datasets are mostly manually captured by the researchers. As we observed in Sec. III and Sec. IV-E target locations are often around the center and target states are mostly stationary or moving slowly in video beginning, which results in unfair comparison. Thus, randomly cropped RGBD videos will alleviate the data bias between video beginning and ending parts, so they are more challenging for trackers. Also, RTRE is effective to evaluate the tracker’s robustness and data bias.

B. Evaluation protocols

A wealth of performance measures have been proposed for RGBD tracker evaluation, but they are proposed accompanied by different datasets with different characteristics. For example, STC employs evaluation metrics from OTB and VOT, which are both determined to short-term tracking and not suitable for long-term tracking. CDTB’s and DepthTrack’s evaluation systems are modified from long-term tracking, requiring the trackers to report both bounding box and confidence score which early trackers cannot. Thus, a unified evaluation protocol is necessary which can clearly reflect different aspects of tracking. Therefore, RGBD tracking requires measures to...
allow easy interpretation and tracker comparison with a well-defined tracker equivalence.

C. Model design

1) New paradigm: Novel paradigms have been introduced into many vision tasks, including RGB-based object tracking. For example, the modified version of the transformer-based RGB tracking model STARK [69] shows extraordinary performance on RGBD tracking, which indicates that the novel paradigm is of importance in multi-modal tracking. Therefore, importing novel paradigms from related areas is of potential.

2) Cross-modal fusion: It is important to effectively fuse RGB and depth information in RGBD tracking. Existing tracking models mostly employ heuristic fusion strategies, e.g., the weighted sum between two modalities, modality selection, and joint distribution. Effective trainable deep features and fusion modules are required.

3) Model efficiency: As object tracking is a real-time application, tracking speed is an important measure, which is ignored in RGBD tracking for a long time. We notice that most RGBD trackers’ speed is out of real-time requirement. When VOT participants obtain good performance on the hybrid datasets and several sub-tests, their speed is relatively low. Getting a good trade-off between performance and speed is still challenging to RGBD model design. Lightweight architectures are required for real-world applications.

4) Model robustness: From experiments, we observed that, although deep models show high tracking performance, they are not robust to both spatial and temporal perturbations, which may prevent the models to be used in real-life applications. Also, adversarial attacks and the defense of RGBD tracking algorithms are required to be studied. We hope our observations will shed light on the model robustness research.

VI. Conclusions

In this paper, we present a comprehensive review of RGBD tracking. To this end, we first provide taxonomies for categorizing RGBD tracking models, including depth usage, heuristic/deep models, and RGBD fusion. Then, we cover the popular datasets in RGBD tracking and review the related evaluation metrics. Next, by offering a hybrid dataset containing the public RGBD tracking sequences, we can evaluate 18 RGBD trackers for performance benchmarking. Most importantly, we conduct extensive experiments and provide in-depth analysis on the representative trackers from overall performance, depth data quality, long-term settings, attribute-based tests, and robustness evaluation. Finally, discussions on dataset construction, evaluation protocols, and model design are given for further research.

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