Grounding-Tracking-Integration

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Abstract

In this paper, we study tracking by language that localizes the target box sequence in a video based on a language query. We propose a framework called GTI that decomposes the problem into three sub-tasks: Grounding, Tracking and Integration. The three sub-task modules operate simultaneously and predict the box sequence frame-by-frame. “Grounding” predicts the referred region directly from the language query. “Tracking” localizes the target based on the history of the grounded regions in previous frames. “Integration” generates final predictions by synergistically combining grounding and tracking. With the “integration” task as the key, we explore how to indicate the quality of the grounded regions in each frame and achieve the desired mutually beneficial combination. To this end, we propose an “RT-integration” method that defines and predicts two scores to guide the integration: 1) R-score represents the Region correctness whether the grounding prediction accurately covers the target, and 2) T-score represents the Template quality whether the region provides informative visual cues to improve tracking in future frames. We present our real-time GTI implementation with the proposed RT-integration, and benchmark the framework on LaSOT and Lingual OTB99 with highly promising results. Moreover, a disambiguated version of LaSOT queries can be used to facilitate future tracking by language studies.

1. Introduction

Given a video and a language query, tracking by language [18] is the task of predicting the box sequence of the referred object based on the input language query, as shown in Figure 1 (a). The grounded box sequences are predicted sequentially in each frame of the input video. Compared to specifying the target by drawing a box as in object tracking [14, 30, 31, 34], providing a language query is a natural way of human-computer interaction. The language specification provides the clear semantic meaning of the target and thus alleviates certain failures in object tracking caused by appearance changes, occlusion, box drifting and so on. Tracking by language also opens up applications such as

![Figure 1. Tracking by language](image)

Naturally, two kinds of information are available in tracking by language. On the one hand, the language query contains target specifications in all frames. On the other hand, the history of the grounded image patches in previous frames provides cues for the target. Therefore, tracking by language can be approached either from language referring (“grounding”) or visual patch matching (“tracking”) perspectives. For the first perspective, “grounding” approaches the problem by processing each frame independently. However, “grounding” methods frequently fail in frames of degraded visual qualities. The grounded regions also tend to be inconsistent throughout time, as no neighboring similarities in videos are exploited. For the second perspective, “tracking” localizes the region based on a given box in previous frames. When initialized with an ideal given box (by grounding), “tracking” generally provides tubelets of better qualities than “grounding”. However, “tracking” suffers from bad initialization when the language grounded region either refers to the incorrect object or does not contain informative visual cues of the target for tracking.
This study builds on the understanding that neither “grounding” nor “tracking” alone solves the tracking by language problem, while the combination can possibly compensate for each other’s weaknesses. “Tracking” has the potential to correct “grounding” failures based on the information from adjacent frames, whereas “grounding” could improve “tracking” by re-initializing the tracker with better language grounded regions.

In this study, we propose a GTI framework, where we decompose the tracking by language task into three sub-tasks: Grounding, Tracking and Integration. Given a frame, “grounding” localizes the region directly from the input language query. “Tracking” makes the prediction by using the history of grounded regions as tracking templates, i.e. the “tracking” predicted region should be visually similar to the region in tracking templates. “Integration” combines the two perspectives in a mutually beneficial way to obtain better final predictions. As shown in Figure 1 (b), “integration” selects whether “grounding” or “tracking” is more important in each frame, and generates the final box prediction accordingly. In frames where “grounding” is assigned higher importance, the language grounded region is included in the region history to help “tracking” in future frames. The three modules function simultaneously and generate tubelet predictions frame-by-frame.

Criteria for integration. While a wide range of “grounding” [22, 33, 35, 36] and “tracking” [5, 16, 17] methods exist, the “integration” problem is unique in tracking by language and we are not aware of any proper method that can be directly applied. “Integration” with pre-defined rules or fixed weights in all frames [18] generally shows limited performance. Because such naive methods operate independently of the per-frame context and grounded regions, they neither manage to localize and correct grounding failures with tracking results, nor strengthen future tracking with selected good language grounded regions. Instead, the “integration” module should operate adaptively in each frame by referencing the corresponding visual input, language query and grounded region. To be specific, a good “integration” module should satisfy the following criteria: 1) The module should predict if the grounded region accurately covers the target, and assign higher importance to “grounding” in such frames. 2) The module should predict if the grounded region contains informative visual cues of the target that could improve the tracker, and include such region into the object history. 3) The module should be light-weighted and fast.

Mechanism for integration. We propose a new paradigm for the “integration” problem named RT-integration. In each frame, two scores are predicted to guide the “integration”. R-score reflects the Region correctness, i.e. whether the grounded region accurately covers the language referred target. T-score reflects the Template quality, i.e. whether the grounded region contains discriminative visual cues to help tracking. High RT-scores indicate the high importance of “grounding”. In such frames, we take “grounding” predictions both as the outputs and future tracking templates, whereas in the remaining frames the “tracking” prediction is adopted as the outputs to correct possible grounding failures. We derive the ground-truth RT-scores from box annotations and train a separate module for RT-score prediction.

Finally, we present our real-time implementation of the GTI framework with the proposed RT-integration. We benchmark the proposed framework on LaSOT [8] and Linguat OTB99 [18] with highly promising results. As the original language queries in LaSOT can be ambiguous [8], we clean the dataset by replacing the ambiguous language queries with new annotations. Our contributions are:

- We propose a Grounding-Tracking-Integration (GTI) framework for tracking by language.
- We propose “RT-integration” that adaptively integrates grounding and tracking with region correctness scores and template quality scores predicted in each frame.
- Our real-time implementation of the GTI framework shows highly promising results on multiple datasets.
- We clean up the ambiguous queries in LaSOT [8] to facilitate future tracking by language studies.

2. Related Work

Tracking with box specifications. Tracking returns the tubelet of the specified object in a video. Our study is related to the traditional object tracking [14, 30, 31, 34], where the ground-truth box in the first frame (the tracking template) is used to specify the object of interest. Correlation filter based methods [6, 7, 10] show good efficiency and accuracy on the task. Recently, the Siamese network based trackers [1, 16, 17] also show promising performance. In this study, we study the problem of using language queries to replace boxes as the target specification.

Tracking with language cues. Several previous studies explore tracking with language cues [8, 18, 26, 29]. Wang et al. [29] adopt language queries as the extra information alongside with boxes for tracking. LaSOT [8] is a recently proposed large scale tracking dataset that has auxiliary language query annotations. Li et al. [18] first introduce the tracking by language task and proposes a Linguat Specification Attention Network (LSAN). The authors encode the region history and language query as the parameters for two independent dynamic filters, and generate per-frame tracking and grounding predictions accordingly. The predictions are then fused with a fixed weight in all frames. We later show that LSAN is a special case of the GTI framework with a naive integration module.

Visual grounding. Visual grounding [13, 22, 36] is the task of localizing the referred region in an image given a language query. Most previous methods [21, 25, 28, 35, 37]
follow a two-stage pipeline, where a number of region candidates are first detected, followed by a language-based ranking stage to find the most relevant region. The recently proposed one-stage methods [3, 33] conduct visual-textual fusion at image level and improve both the accuracy and inference speed.

**Learning to predict localization confidence.** Our proposed “RT-integration” module is related to previous studies on learning localization confidence. In object tracking, ATOM [4] predicts the Intersection over Union (IoU) between the tracking output and the ground-truth target by taking tracking templates as references. Our method is more relevant to IoU prediction in object detection [12] and instance segmentation [11], where no template references are available. IoU-Net [12] proposes an IoU prediction module with an R-CNN [9] like structure on top of the detection backbone [19] to predict the localization confidence. MS R-CNN [11] extends the idea for instance segmentation. Going beyond localization confidence prediction based on the objectness, the “integration” task in tracking by language poses extra requirements of 1) predicting visual-textual similarity, 2) predicting template quality and 3) being fast.

### 3. Grounding-Tracking-Integration

Given a natural language query for a video, we hope to return the box sequence of the referred object. Different from object tracking [16, 17], the references are specified by a language query instead of the ground-truth bounding box in the first frame. We propose a Grounding-Tracking-Integration (GTI) framework to approach the problem. As shown in Figure 2, the three modules operate simultaneously and generate box predictions frame-by-frame. In each frame, “grounding” takes the frame and language query as input for object localization. “Grounding” operates independently in each frame and does not accumulate errors. However, it may fail due to the errors of grounding methods. “Tracking” predicts the box based on the history of language grounded regions. When provided a correct region in nearby frames as the template, “tracking” generally generates better box predictions than “grounding”. However, “tracking” often accumulates the error from the given template, and decreases in performance when the temporal distance between the template and current frame increases. “Integration” looks at both grounding and tracking predictions, and generates the final prediction.

### 4. RT-Integration

We investigate the “integration” task in the GTI framework. The goal of this sub-task is to combine “grounding” and “tracking” in a mutually beneficial and overall synergistic way to generate better final predictions. In frames where “grounding” predictions are of good qualities, including such grounded regions into tracking templates strengthens the tracker for future frames. In the remaining frames where “grounding” is likely to fail, adopting the “tracking” prediction generally leads to better final predictions. To achieve such a mutually beneficial combination, “integration” should predict when “grounding” is of good quality or likely to fail, and adjust the grounding-tracking importance in each frame accordingly.

The core idea of our proposed RT-integration is to represent the grounding and tracking importance in each frame as two scores, namely the RT-scores, where higher score values indicate the better quality and thus higher importance of “grounding.” The R-score reflects if the grounded region precisely covers the target, and the T-score shows if the grounded region contains visual cues that can improve the tracker. In frames with high RT-scores, the “grounding” prediction is selected as the output and used to update the tracker, whereas the remaining frames are processed by “tracking”. This study focuses on how to properly define and precisely predict the RT-scores.

A separate module is trained in a fully supervised way to predict the RT-scores as shown in Figure 2. The input to the module is the visual-textual feature and the language grounded region in a frame and the output is the corresponding RT-score prediction as shown in Figure 3. During training, the ground-truth RT-scores are derived from the box annotations and are used to train the module. Essentially, “integration” can be regarded as a self-judge process for the framework to examine whether the language grounded region in a frame is valid as the output and new template. Section 4.1 introduces the definition of the derived RT-scores. Section 4.2 presents the details of the module architecture and training procedure. During inference, RT-scores are predicted with the trained module in each frame, and are adopted to guide the adaptive integration that synergistically combines grounding and tracking to generate final predictions. Section 4.3 introduces the RT-score-guided adaptive integration in each frame. A complete inference pipeline of the GTI framework is presented in Section 5.

#### 4.1. RT-scores

Two factors are essential for an ideal “integration”. First, “integration” should predict if the language grounded re-
We obtain the ground-truth T-score by conducting tracking with a fixed tracker [16]. To be specific, we initialize the tracker with the ground-truth target region in a given frame, and conduct tracking in all remaining frames. With the fixed tracker and the almost identical tracking video (except the given template frame itself), the only variable is the quality of the template patch in the given frame. Therefore, the obtained mIoU score reflects the desired template quality and is adopted as the ground-truth T-score.

4.2. Score prediction

We next introduce the proposed module for RT-scores prediction. In each frame, the module refers the frame, query and grounded box to generate the RT-score prediction. We re-use the fused feature from “grounding” as the per-frame visual-textual representation to boost the inference speed. As shown in Figure 3, the proposed module takes the grounded region and the fused visual-textual feature from “grounding” [33] as inputs, and predicts the scores for the grounded region. The module consists of three stand-alone $1 \times 1$ convolutional layers. The RT-scores in the same spatial location as the top-1 “grounding” prediction is output as the final score prediction.

The score prediction module is trained separately from “grounding” and “tracking”. The R- and T-score predictions are modeled as two separate regression problems where the smoothed-L1 loss is adopted. With a pre-trained grounding model [33], we generate training samples by collecting the triplets of visual-textual features, grounded regions and derived RT-scores. During training, we filter out the samples with a grounding confidence score less than 0.5. Such grounded regions are likely to be incorrect and can be well identified by grounding confidences. We find the filtering simplifies the score prediction problem and empirically leads to better performances. During inference, we consider such region incorrect and directly set the R-score to 0.
4.3. Adaptive integration

With the RT-scores predicted, the adaptive integration can be conducted in various ways, for example score-guided fusion or hard switching between grounding and tracking. We present a vanilla version of hard switching. First, the R- and T-scores are multiplied in each frame to obtain a unified score that guides “integration”. “Grounding” is considered more important whenever the predicted unified score is higher than the previously saved highest value. In such frames, the grounding prediction is adopted both as the output and to update the template, whereas tracking predictions are taken in the remaining frames.

With the same set of importance scores, we find the exact score-guided fusion method such as soft weighted fusion or hard switching has no major influence on the final performance. Instead, a good “integration” method should first be adaptive based on the per-frame context and prediction quality, and more importantly, properly defines and predicts the importance scores to guide integration. We present related experiments in supplementary materials.

5. Implementation of GTI

In this section, we present our real-time implementation of the GTI framework. We introduce the adopted “grounding” and “tracking” modules, as well as the overall pipeline. Grounding. Given a frame, the “grounding” module predicts a region based on the language query. We adopt the one-stage visual grounding [33] as the grounding module in our implementation because of its state-of-the-art accuracy and real-time inference speed. The grounding method merges language and spatial features into YOLOv3 [23] for visual grounding. DarkNet-53 [23] and feature pyramid network [19] are used to encode the visual feature. With an input resolution of 256 × 256, the three feature pyramid heads have the spatial resolutions of 8 × 8, 16 × 16 and 32 × 32, respectively. Similar to one-stage object detection [23], the grounding method outputs multiple box predictions at each of the 8 × 8 + 16 × 16 + 32 × 32 = 1344 locations. With three anchor boxes predicted at each location, the method outputs 3 × 1344 = 4032 grounding predictions per frame. Each predicted region consists of five values, i.e. the relative position, width, height and the confidence score. The prediction with the highest confidence score is output as the final grounded region in each frame.

Tracking. Given a frame, the “tracking” module localizes the target based on the language grounded region history in previous frames. We adopt the SiamRPN++ [16] as the tracker in our implementation while various other object tracking methods [2, 4] can also be directly applied. SiamRPN++ is a Siamese network based tracker that models tracking as the feature cross-correlation between the tracking template and the current frame.

Inference. We then present the inference pipeline on a testing video in Algorithm 1. Given no region history is available in the first frame, the “grounding” result is directly adopted as the output and used to initialize “tracking”. The predicted RT-scores are also saved. In all the following frames, the three modules operate simultaneously. “Integration” predicts the RT-scores in a frame and compare it to the saved value. Whenever a higher score appears, “grounding” is adopted as the output. The tracking template T and the saved score S are also updated in such frames. In the remaining frames, “tracking” is adopted as the output.

6. Experiments

6.1. Datasets

LaSOT. LaSOT [8] contains 1,400 videos with auxiliary language queries. We follow the split [8] that uses 1,120 videos for training and 280 videos for testing. The averaged video length is around 2,500 frames. In the original LaSOT dataset [8], the lingual description is designed as the auxiliary information to help object tracking and does not guarantee to have distinguishable specification alone. To facilitate the study, we clean the dataset by replacing the ambiguous language queries with new annotations. 322 out of the 1,400 language queries are updated. Examples are shown in Figure 5. The annotation procedure, examples and updated queries are provided in supplementary materials.

Linguistic OT99. Linguistic OTB99 [18] augments the OTB100 object tracking dataset [20, 30] with natural lan-
guage descriptions. One query is annotated per target object. We follow the training/testing split [18] that uses the OTB51 videos for training and the remaining 48 videos for testing. The averaged video length is around 600 frames. Lingual ImageNet videos. The targets and videos in the Lingual ImageNet videos dataset [18] are far from real and oversimplify the problem, and thus not suitable for study. Analyses are included in supplementary materials.

6.2. Implementation details

Evaluation criteria. We evaluate the methods with precision and success scores [31]. The precision score reflects the percentage of frames where the estimated location falls within a given threshold of 20 pixels with the target. The success plot shows the ratio of success frames under an IoU threshold ranging from 0 to 1. The area under curve (AUC) of the success plot represents the averaged success rates with different sampled thresholds and is used for evaluation. We follow online tracking that only the previous and current frames are observed for prediction.

Training details. We train the score prediction module in RT-integration separately from the grounding and tracking modules. The three convolutional layers in the score prediction module have \( D = 512, 256, 6 \) output channels, respectively. We train the model with RMSProp [27] and use a batch size of 32. The initial learning rate is \( 10^{-4} \) and follows a linear schedule. We fine-tune the grounding module [33] pre-trained on Flickr30K Entities [22] with training set videos. For the tracking module, we use the models released by SiamRPN++ [16] and fix the weights. The decay rate in Algorithm 1 is set to 0.998.

6.3. Experiment protocols

Table 1 reports the tracking results on LaSOT [8] and Lingual OTB99 [18]. One-stage grounding [33] is used for “grounding” and SiamRPN++ [16] is used for “tracking” in all reported results except the original LSAN [18]. We list in the “Integration guidance” column the different integration methods. The top portion of Table 1 contains naive integration with either pre-defined scheduling rules or fixed fusion weights. Frame indices such as “all”, “first” and “fixed interval” indicate pre-defined scheduling is adopted and on which frames grounding is assigned higher importance. The bottom portion of the table contains the results of our adaptive integration methods. The types of adopted importance scores are listed in “Integration guidance”.

Various baselines and state-of-the-art methods are experimented and compared. To be specific, we systematically study the following settings:

- **Visual grounding.** One could attempt to approach tracking by language by processing each frame independently by grounding. One-stage visual grounding [33] is adopted for the experiment.
- **First frame tracking.** By taking the grounded region in the first frame as the tracking template, tracking by language is converted to an object tracking problem. This baseline is referred to as “First frame tracking”.
- **Middle/Last/Random frame tracking.** We initialize the tracker with the grounded region in the middle, last or one random sampled frame.
- **Fixed interval tracking.** In this baseline, “grounding” is assigned higher importance with a fixed temporal interval. We design the fixed interval to be similar to the averaged frequency of our adaptive integration.
- **LSAN/LSAN++.** We compare to the state-of-the-art tracking by language method LSAN [18]. For a fair comparison, we strengthen LSAN with stronger grounding [33] and tracking [16] backbones used in other experiments, and refer to it as “LSAN++”.
- **Ours-Grounding score.** We use the confidence score generated by “grounding” to guide the integration. “Ours-” indicates that the GTI implementation in Section 5 is adopted, except the integration is guided by grounding confidences instead of predicted RT-scores. Finally, we present the performance of the GTI framework with our proposed RT-integration and its variations.

6.4. Tracking by language results

Lingual OTB99. Tracking by language with the “grounding” module only generates a success score of 0.442. Approaching the task by mostly relying on “tracking” obtains comparable results of around 0.434 as shown in “First/middle/last/random frame tracking”. “Integration” aims at improving the tracking by language performance by synergistically combining the two modules. Fixed temporal scheduling is one possible solution that switches between grounding and tracking with a fixed interval, and slightly improves the success score (cf. “Fixed interval tracking”). Fusing the two modules’ predictions in each frame with a fixed weight in all frames is another approach as conducted in “LSAN” [18]. “LSAN++” improves the success score from the originally reported 0.259 to 0.449 with the strengthened backbones, and slightly outperforms the “Visual grounding” baseline. Nonetheless, limited improvements of less than 0.01 are observed on all naive integration methods when compared to the grounding baseline. This indicates that “integration” with fixed weights in all frames or pre-defined scheduling rules is ineffective.

In this study, we propose to guide “integration” with a kind of importance scores adaptively predicted from the corresponding frame, language query and box. One intuitive choice of the importance score is the grounding confidences. “Ours-Grounding score” reports a success score...
of 0.532, which is significantly better than the grounding baseline of 0.442 and the naive integration of 0.449. We continue exploring more effective and interpretable score indications. With the proposed RT-integration, our method and its variations outperform the compared methods by a large margin. “Ours-R score” achieves a success score of 0.565, compared to the 0.449 by LSAN++ and the 0.449 by fixed interval tracking. By jointly considering the template quality score, the success score is further improved.

**LaSOT.** The results on LaSOT are organized in the same way as Linguat OTB99. Using “grounding” only provides a baseline success score of 0.416. The tracking baseline provides a lower performance of 0.361. This is because a longer averaged video length in LaSOT makes tracking more challenging. Because of the same reason, updating the template multiple times performs better than a single template frame (cf. different intervals in “Fixed interval tracking”). To eliminate the influence of the template update frequency, we design the “Fixed interval tracking” to have a similar frequency as our RT-integration, which ranges from 5 to 20 frames. For a reference, “Ours-Grounding score/Ours-R score/Ours-RT score” assign higher weights to “grounding” every 17.0/20.6/23.5 frame on LaSOT and 7.9/13.8/16.6 frame on Linguat OTB99. By eliminating the influence of the template update frequency, we show that our adaptive integration performs better purely by more effective combining grounding and tracking.

We draw from LaSOT about the same observation on “integration” as from Linguat OTB99. The naive integration methods such like “LSAN++” and “fixed interval tracking” show limited improvements from the “grounding” baseline, while the adaptive integration significantly improves the performance. Our proposed RT-integration method achieves a success score of 0.478, compared to the 0.404 by LSAN++ and the 0.423 by fixed interval tracking. This indicates the effectiveness of our proposed RT-integration and the importance of adaptive integration.

**Inference speed.** A fast inference speed is important for tracking by language. We evaluate the inference speed of our GTI implementation on a desktop with Intel Core i9-9900K@3.60GHz and NVIDIA 1080TI. Our framework runs at around 20 fps, where the grounding module takes around 20ms and the tracking module takes around 30ms. The proposed RT-integration module takes less than 1ms by reusing the visual-textual features from grounding.

**Ablation study.** We conduct extensive ablation studies to analyze the influences of different framework components. To be specific, we first experiment with how the quality of “grounding” and “tracking” influence the final performance of GTI. We then focus on “RT-integration” and test different score-guided integration methods. We conclude that stronger modules generally lead to better overall performance. Given the same set of per-frame importance scores, different score-guided integration methods generate comparable results. Therefore, how to obtain the importance score is the key for good “integration”, instead of how to combine grounding and tracking with the obtained scores. We present the results and analyses in supplementary materials.

### 6.5. Qualitative results analyses

In this section, we first compare the success and failure cases of the methods with naive integration modules as well as ours, to show the significance of our proposed RT-integration. We show representative examples in Figure 6. First, our method (silver boxes) are more stable and accurate when compared to per-frame visual grounding outputs (blue boxes). Including “tracking” (dark grey boxes) generates more stable results by exploiting the cross-frame visual similarity. However, the grounded region for tracker initialization in a randomly selected frame might be incorrect and thus fails “tracking” in the following frames. Figures 6 (a) and (b) show failure cases for the “First frame tracking” that our method can solve. “Ours - Grounding score” guides integration with grounding confidences and thus generates
much better results. Nonetheless, our proposed RT-scores are more effective in guiding integration. Figures 6 (c) and (d) present challenging cases where “grounding” fails in most frames. When all compared methods fail, our RT-integration successfully combines grounding and tracking to provide mostly correct tracking results throughout the video. Overall, our proposed approach performs better by more effectively integrating grounding with tracking.

Despite the effectiveness of our proposed integration, when grounding fails on all frames, there is no hope to get correct results (cf. Figure 6 (e)). RT-score estimation may also be incorrect. Figure 6 (f) shows an example where grounding does make the correct prediction in the second frame but our method fails to predict the correct RT-scores and correct the errors in such frames. In fact, this is the cause for the gap from the oracles in Table 2.

### 6.6. Oracle analyses

Tracking by language is generally more challenge than the conventional tracking by gt box task, and tends to perform worse on the same video [18]. The proposed RT-integration greatly improves the tracking by language performance, but meanwhile the score prediction module introduces new errors and potentially limits the framework’s performance. In this section, we experiment the upper bound of the GTI framework that has an ideal “integration” model, given the status quo of grounding [33] and tracking [16]. The oracle is compared to both tracking by language and by gt box. To be specific, we compare the following settings:

- **Tracking by gt box.** With the same dataset split, tracking by ground-truth box [5, 16, 17] serves as an upper bound of tracking with ideal target specifications.
- **Ours-R-oracle.** We design two oracle analyses with the same GTI implementation in Section 5. The R-score in the oracle analyses is calculated with the ground-truth box at each frame instead of predicted.
- **Ours-RT-oracle.** “Ours-RT-oracle” considers both the region correctness and template quality scores.

As shown in Table 2, the GTI framework with an ideal integration module achieves comparable (on shorter videos [18]) or better (on longer videos [8]) performance than the state-of-the-art tracker [16]. This shows that it is possible for tracking by language to achieve comparable results to tracking by box given the status quo of grounding and tracking, despite a more challenge setting. On the other hand, the gap between the results of the oracle GTI and our implementation shows the integration problem is non-trivial, and motivate us to develop better integration methods in future studies. Finally, with the continuously improving grounding and tracking methods, we expect the future GTI frameworks with stronger modules to further improve the tracking by language performances.

### 7. Conclusion

We propose a GTI framework for tracking by language where we decompose the task into three sub-tasks: grounding, tracking and integration. We focus on the key sub-task of “integration” that synergistically combines grounding and tracking, and propose an RT-integration module that defines two scores to guide integration in each frame. The R-score represents the region correctness and the T-score represents the template quality. We benchmark our real-time implementation of the GTI framework on LaSOT and Lingual OTB99 to demonstrate highly promising results.
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In this supplementary document, we present extra details that couldn’t be fit in the main paper. In Section A, we introduce the statistics and annotation procedures for the disambiguated LaSOT queries. In Section B, we conduct the ablation studies on different score-guided integration methods and different grounding and tracking modules in GTI. In Section C, we discuss why the Lingual ImageNet videos dataset [18] used in a previous study [18] is not suitable for tracking by language. Finally in Section D, we provide the video indexes for the presented qualitative results in the main paper.

Appendix A. Disambiguated LaSOT

The original LaSOT dataset [8] contains auxiliary language queries that might contain ambiguous target specifications. For example in Figure 7 (a), the referred glass cannot be distinguished based on the original query. To facilitate tracking by language studies, we clean the LaSOT queries by replacing the ambiguous queries with new annotations. In the first step, annotators are presented with the video, target tubelet and the original language query in LaSOT, and are asked to label if the target can be distinguished based on the original query. The collected annotations show that 322 out of the 1,400 videos contain ambiguous queries. Annotators are then suggested to provide new queries that have clear target specifications. Extra descriptions of the target’s location, color, size, relationships are included in the cleaned queries. Among the 322 updated queries, 80 samples might still be ambiguous, i.e., in the verification step at least one out of two annotators cannot distinguish the target based on the new query. This is because some videos and targets are not proper for tracking with natural language specifications (e.g. Figures 7 (g) and (h)).

We provide representative examples of the updated queries in Figure 7. Extra location descriptions are added to Figures 7 (a) and (b) to disambiguate the query. Color and entity descriptions are included in Figures 7 (c) and (d) to provide the target specification. Relationships and other detailed descriptions are provided in Figures 7 (e) and (f) to generate a clear target specification. After the manual annotation, a small portion of samples is still ambiguous that the language query alone cannot generate clear specifications for the given target. For example, in Figures 7 (g) and (h), visually similar objects exist and make language referring difficult.

Appendix B. Ablation studies

In this section, we conduct extensive ablation studies on the GTI framework. We first test the GTI implementation with different “grounding” and “tracking” modules. We then focus on the “RT-integration” and examine different adaptive integration methods.
Table 3. Tracking by language results with different grounding and tracking modules on Lingual OTB99.

| Method                  | Grounding          | Tracking     | Lingual OTB99 |
|-------------------------|--------------------|--------------|---------------|
|                         |                    |              | Succ.         | Prec.         |
| Visual Grounding        | Onestage-light     | None         | 0.379         | 0.491         |
| Fixed interval tracking | Onestage-light     | SiamRPN++    | 0.391         | 0.492         |
| Fixed interval tracking | Onestage-light     | SiamRPN++    | 0.449         | 0.554         |
| Ours-RT scores          | Onestage-light     | SiamRPN++    | 0.570         | 0.723         |
| Ours-RT scores          | Onestage-light     | SiamRPN++    | 0.581         | 0.732         |

Table 4. Tracking by language results with different score-guided integration methods on Lingual OTB99.

| Template            | Product Succ. | Product Prec. | Average Succ. | Average Prec. | Weighted Sum Succ. | Weighted Sum Prec. |
|---------------------|---------------|---------------|---------------|---------------|--------------------|--------------------|
| Naive replacement   | 0.672         | 0.863         | 0.673         | 0.863         | 0.665              | 0.847              |
| Improve. thres.     | 0.632         | 0.814         | 0.619         | 0.799         | 0.627              | 0.812              |
| Weighted update     | 0.675         | 0.867         | 0.676         | 0.867         | 0.665              | 0.848              |
| Score weighted      | 0.668         | 0.856         | 0.663         | 0.846         | 0.674              | 0.854              |

Appendix C. Lingual ImageNet videos

The Lingual ImageNet videos dataset [18] augments the ImageNet Video Object Detection dataset [24] with one query per target object. We follow the same split [18] that uses 50 videos for training and the other 50 for testing. The averaged video length is around 270 frames.

The same experiments in the main paper are conducted on Lingual ImageNet videos. We find that the Lingual ImageNet videos dataset is a special easy case, where current visual grounding methods already perform better than tracking by boxes (“Visual grounding” success score: 0.864, “SiamRPN++ [16]”: 0.768). In Lingual ImageNet videos, the target objects are mostly in the center of the frame and few distracting objects exist, which makes the task easy for visual grounding. Despite the good results on this specific dataset, such videos are far from real and oversimplify the tracking by language problem.

Appendix D. Video examples

We provide the video indexes for the presented qualitative examples in the main paper (Figure 6).