Occluded Video Instance Segmentation

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Abstract

Can our video understanding systems perceive objects when a heavy occlusion exists in a scene?

To answer this question, we collect a large scale dataset called OVIS for occluded video instance segmentation, that is, to simultaneously detect, segment, and track instances in occluded scenes. OVIS consists of 296k high-quality instance masks from 25 semantic categories, where object occlusions usually occur. While our human vision systems can understand those occluded instances by contextual reasoning and association, our experiments suggest that current video understanding systems are not satisfying. On the OVIS dataset, the highest AP achieved by state-of-the-art algorithms is only 14.4, which reveals that we are still at a nascent stage for understanding objects, instances, and videos in a real-world scenario. Moreover, to complement missing object cues caused by occlusion, we propose a plug-and-play module called temporal feature calibration. Built upon MaskTrack R-CNN and SipMask, we report an AP of 15.2 and 15.0 respectively. The OVIS dataset is released at http://songbai.site/ovis, and the project code will be available soon.

1. Introduction

In the visual world, objects rarely occur in isolation. The psychophysical and computational studies have demonstrated [31, 15] that our vision systems perceive occluded objects by means of distinguishing actual boundaries of a given object (a.k.a, intrinsic boundaries) from those caused by occlusion (a.k.a, extrinsic boundaries), and then amodally explaining away the missing object cues. As shown in Fig. 1, we are able to complete the intrinsic contours coarsely with contextual reasoning, and sometimes, with prior knowledge.

The question then becomes, can our video understanding systems perceive occluded objects with comparable performance? Our work aims to explore this matter in the context of video instance segmentation, a popular task recently proposed in [49] that targets a comprehensive understanding of objects in videos. To this end, we explore a new and challenging scenario called Occluded Video Instance Segmentation (OVIS), which requests a model to simultaneously detect, segment and track object instances in occluded scenes.

As the major contribution of this work, we collect a large scale dataset called OVIS, specifically for video instance segmentation in occluded scenes. While being the second video instance segmentation dataset after YouTube-VIS [49] with 131k masks, OVIS consists of 296k high-quality instance masks out of 25 commonly seen semantic categories. The most distinctive property of our OVIS dataset is that a large portion of objects is under various types of severe occlusions caused by different factors (see Fig. 2 for different types). Therefore, OVIS is a useful testbed to evaluate video instance segmentation models for dealing with heavy object occlusions.

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To dissect the OVIS dataset, we conduct a thorough evaluation of 5 state-of-the-art algorithms whose code is publicly available, including FEELVOS [38], IoUTracker+ [49], MaskTrack R-CNN [49], SipMask [4], and STEm-Seg [1]. However, the experimental results suggest that current video understanding systems fall behind the capability of human beings in terms of occlusion perception. The highest AP is only 14.4 achieved by [1]. In this sense, we are still far from deploying those techniques into practical applications, especially considering the complexity and diversity of scenes in the real visual world.

To address the occlusion issue, we also propose a simple baseline module called temporal feature calibration. For a given query frame in a video, we resort to a reference frame to complement its missing object cues. Specifically, the proposed module learns a calibration offset for the reference frame with the guidance of the query frame, and then the offset is used to adjust the feature embedding of the reference frame via deformable convolution [8]. The refined reference embedding is used in turn to assist the object recognition of the query frame. Our module is a highly flexible plug-in. While applied to MaskTrack R-CNN [49] and SipMask [4] respectively, we report an AP of 15.2 and 15.0, significantly outperforming the corresponding baselines by 2.6 and 2.9 in AP respectively.

To summarize, our contributions are three-fold:

- We advance video instance segmentation by releasing a new benchmark dataset named OVIS (short for Occluded Video Instance Segmentation). OVIS is designed with the philosophy of perceiving object occlusions in videos, which could reveal the complexity and the diversity of real-world scenes.

- We streamline the research over the OVIS dataset by conducting a comprehensive evaluation of 5 state-of-the-art video instance segmentation algorithms, which could be a baseline reference for future research in OVIS.

- We propose a plug-and-play module to alleviate the occlusion issue. While applied to MaskTrack R-CNN [49], we report an AP of 15.2 on OVIS and 32.1 on YouTube-VIS respectively, outperforming a series of state-of-the-art methods. When applied to SipMask [4], we report a AP of 15.0 on OVIS and 35.0 on YouTube-VIS.

2. Related Work

Our work focuses on Video Instance Segmentation in occluded scenes. The most relevant work to ours is [49], which formally defines the concept of video instance segmentation and releases the first dataset called YouTube-VIS. Built upon the large-scale video object segmentation dataset YouTube-VOS [47], the YouTube-VIS dataset contains a total of 2,883 videos, 4,883 instances, and 131k masks in 40 categories. Compared with the YouTube-VIS dataset, OVIS aims to construct a more challenging video instance segmentation dataset with severe occlusions.

Since the release of the YouTube-VIS dataset, video instance segmentation has attracted great attention in the computer vision community, arising a series of algorithms recently [49, 4, 1, 2, 27, 30, 41, 11]. MaskTrack R-CNN [49] is the first unified model for video instance segmentation. It achieves video instance segmentation by adding a tracking branch to the popular image instance segmentation method Mask R-CNN [13]. Lin et al. [27] propose a modified variational auto-encoder architecture built on the top of Mask R-CNN. MaskProp [2] is also a video extension of Mask R-CNN which adds a mask propagation branch to propagate masks to adjacent frames, and then tracks instances by the propagated masks. SipMask [4] extends single-stage image instance segmentation to the video level by adding a fully-convolutional branch for tracking instances. Different from those top-down methods, STEm-Seg [1] proposes a bottom-up method, which performs video instance segmentation by clustering the pixels of the same instance. Our method adopts MaskTrack R-CNN [49] and SipMask [4] as the baselines, and endows them with the ability to alleviate object occlusions. By adding the proposed feature calibra-
tion module, the performance is significantly improved in occluded scenes.

Meanwhile, our work is also relevant to several other tasks, including:

**Video Object Segmentation.** Video object segmentation (VOS) is a popular task in video analysis. According to whether to provide the mask for the first frame, VOS can be divided into semi-supervised and unsupervised scenarios. Semi-supervised VOS [40, 19, 25, 34, 16, 18, 35, 26] aims to track and segment a given object with a mask. Many Semi-supervised VOS methods [40, 19, 25] adopt an online learning manner which fine-tunes the network on the mask of the first frame during inference. Recently, some other works [34, 16, 18, 35, 26] aim to avoid online learning for the sake of faster inference speed. Unsupervised VOS methods [24, 42, 37] aim to segment the primary objects in a video without the first frame annotations. Different from video instance segmentation that needs to classify objects, both unsupervised and semi-supervised VOS does not distinguish semantic categories.

**Video Semantic Segmentation.** Video semantic segmentation requires semantic segmentation for each frame in a video. LSTM [10], GRU [33], and optical flow [52] are introduced to leverage temporal contextual information for more accurate or faster video semantic segmentation. Video semantic segmentation does not require distinguishing instances and tracking objects across frames.

**Video Panoptic Segmentation.** Dahun et al. [20] define a video extension of panoptic segmentation [21], which requires generating consistent panoptic segmentation, and in the meantime, associating instances across frames.

**Multi-Object Tracking and Segmentation.** Multi-object tracking and segmentation (MOTS) [39] task extends Multi-Object Tracking (MOT) [36] from a bounding box level to a pixel level. Paul et al. [39] release the KITTI MOTS and MOTSChallenge dataset, and propose Track R-CNN that extends Mask R-CNN by 3D convolutions to incorporate temporal context and an extra tracking branch for object tracking. Xu et al. [48] release the ApolloScape dataset which provides more crowded scenes and proposes a new track-by-points paradigm.

Our work is of course relevant to some image-level recognition tasks, such as semantic segmentation [29, 6, 7], instance segmentation [13, 17, 22], panoptic segmentation [21, 46, 23], large vocabulary instance segmentation [12, 44], etc.

### 3. OVIS Dataset

Given an input video, video instance segmentation requires detecting, segmenting, and tracking object instances simultaneously from a predefined set of object categories.

![Number of instances per category in the OVIS dataset.](image)

An algorithm is supposed to output the class label, confidence score, and a sequence of binary masks of each instance.

The focus of this work is on collecting a large scale benchmark dataset for video instance segmentation with severe object occlusions. In this section, we mainly review the data collection process, the annotation process, and the dataset statistics.

#### 3.1. Video Collection

We begin with 25 semantic categories, including *Person, Bird, Cat, Dog, Horse, Sheep, Cow, Elephant, Bear, Zebra, Giraffe, Poultry, Giant panda, Lizard, Parrot, Monkey, Rabbit, Tiger, Fish, Turtle, Bicycle, Motorcycle, Airplane, Boat, and Vehicle*. The categories are carefully chosen mainly for three motivations: 1) most of them are animals, because movement will lead to severe occlusions, 2) they are commonly seen in our life, 3) these categories have a high overlap with popular large-scale image instance segmentation datasets [28, 12] so that models trained on those datasets are easier to be transferred. The number of instances per category is given in Fig. 3.

As the dataset is to study the capability of our video understanding systems to perceive occlusions, we ask the annotation team to 1) exclude those videos, where only one single object stands in the foreground; 2) exclude those videos with a clean background; 3) exclude those videos, where the complete contour of objects is visible all the time. In the meantime, ensure that each video shall have at least one occlusion type out of *occlusion by object, occlusion by backgrounds, and occlusion by boundaries* (see Fig. 2 for illustrations). Some other objective rules include: 1) video length is generally between 5s and 60s, and 2) video resolution is generally $1920 \times 1080$.

After applying the objective rules, the annotation team delivers 8,644 video candidates and our research team only accepts 901 videos after a careful re-check. It should be mentioned that due to the stringent standard of video collection, the pass rate is as low as 10%.
### Dataset Statistics

| Dataset     | YouTube-VIS | OVIS (ours) |
|-------------|-------------|-------------|
| Masks       | 131k        | 296k        |
| Categories  | 40          | 25          |
| Videos      | 2,883       | 901         |
| Instances   | 4,883       | 5,223       |
| Video duration (s) | 4.63  | 12.77 |
| Instance duration (s) | 4.47  | 10.05 |
| mBOR*       | 0.07        | 0.22        |
| Objects per frame | 1.64  | 4.72        |
| Instances per video | 1.69  | 5.80        |

Table 1. Comparing OVIS with YouTube-VIS in terms of statistics. See Eq. (1) for the definition of mBOR. * means the value of YouTube-VIS is estimated from the training set.

### 3.2. Annotation

Given an accepted video, the annotation team is asked to exhaustively annotate all the objects belonging to the predefined category set. Each object is given an instance identity and a class label. In addition to some common rules (e.g., no ID switch, mask fitness ≤1 pixel), the annotation team is trained with several criteria particularly about occlusions: 1) if an existing object disappears because of full occlusions, then re-appears, the instance identity should keep the same; 2) if a new instance appears in an in-between frame, a new instance identity is needed; and 3) the case of “object re-appears” and “new instances” should be distinguishable by you after you watch the contextual frames therein. All the videos are annotated per 5 frames, which results in that the granularity ranges from 3 to 6 fps.

Each video is handled by one annotator to get the initial annotation, and the initial annotation is then passed to another annotator to check and correct if necessary. The final annotations will be examined by our research team and sent back for revision if deemed below the required quality.

While being designed for video instance segmentation, it should be noted that OVIS is also suitable for evaluating video object segmentation in either a semi-supervised or unsupervised fashion, and object tracking since the bounding-box annotation is also provided. The relevant experimental settings will be explored as part of our future work.

### 3.3. Dataset Statistics

As YouTube-VIS [49] is the only dataset that is specifically designed for video instance segmentation nowadays, we analyze the data statistics of our OVIS dataset with YouTube-VIS as a reference in Table 1. Note that some statistics, marked with *, of YouTube-VIS is only calculated from the training set because only the annotation of the training set is publicly available. Nevertheless, considering the training set occupies 78% of the whole dataset, those statistics could still reflect the properties of YouTube-VIS roughly.

In terms of basic and high-level statistics, OVIS contains 296k masks and 5,223 instances, which is larger than YouTube-VIS that has 131k masks and 4,883 instances. Nonetheless, OVIS has fewer videos than YouTube-VIS as our design philosophy favors long videos and instances so as to preserve enough motion and occlusion scenarios.

As is shown, the average video duration and the average instance duration of OVIS are 12.77s and 10.05s respectively. Fig. 4(a) presents the distribution of instance duration, which shows that all instances in YouTube-VIS last less than 6s. Long videos and instances increase the difficulty of tracking and the ability of long-term tracking is required.

As for object occlusions, it is somewhat problematic to quantitatively measure the degree. To remedy this, we define a metric named Bounding-box Occlusion Rate (BOR). Given a video frame with $N$ objects denoted by bounding boxes $\{B_1, B_2, \ldots, B_N\}$, we compute the BOR for this frame as

$$\text{BOR} = \frac{\left| \bigcup_{1 \leq i < j \leq N} B_i \cap B_j \right|}{\left| \bigcup_{1 \leq i \leq N} B_i \right|},$$

where the numerator means the area sum of the intersection between any two or more bounding boxes. In other words, we exclude those positions which only appear in an individual bounding box. The denominator means the area...
of the union of all the bounding boxes. An illustration is given in Fig. 5, which shows the larger the BOR value is, the heavier the occlusion is.

Then we utilize mBOR, the average value of BORs of all the frames in a dataset (frames that do not contain any objects are ignored), to characterize the dataset in terms of the occlusion. As shown in Table 1, the mBOR of OVIS is 0.22, much higher than that of YouTube-VIS 0.07. The BOR distribution is further compared in Fig. 4(b). As can be seen, most frames in YouTube-VIS are located in the region where BOR ≤ 0.1 and a small number of frames’ BOR are greater than 0.1. In comparison, the BOR of about half frames in OVIS is no less than 0.2. It supports the focus of our work, that is, to explore the ability of video instance segmentation models in handling occlusion scenes. However, it should be mentioned here that BOR cannot involve all the occlusion types shown in Fig. 2, but is mainly targeted at occlusion by objects. Therefore, mBOR could serve as an effective indicator for occlusion degrees, but only reflect the occlusion degree in a partial or rough way.

In addition to long videos&instances and severe occlusions, OVIS features crowded scenes, which is a natural effect of heavy occlusions. OVIS has 5.80 instances per video and 4.72 objects per frame, while those two values are 1.69 and 1.64 respectively in YouTube-VIS. The comparison of the two distributions is further depicted in Fig. 4(c) and Fig. 4(d).

4. Proposed Approach

We build our method based on MaskTrack R-CNN [49], considering it is the official baseline approach released along with the YouTube-VIS dataset while being a representative of algorithms in this field. In this section, we first revisit MaskTrack R-CNN briefly, then elaborate the details of our method. Note that our method is also compatible with other video instance segmentation models (e.g., SipMask [4]) and refer to the experiments for details.

4.1. MaskTrack R-CNN Revisited

Based on Mask R-CNN [13], MaskTrack R-CNN fulfills video instance segmentation by leveraging four branches. Basically, the three branches for object classification, bounding box regression, and mask generation keep the same as Mask R-CNN, which are applied to every single frame. The fourth tracking branch is responsible for tracking objects across frames. Suppose there are N instances identified from previous frames, the candidate box i in the current frame will be assigned to the label n, with the assignment probability defined as

\[
p_i(n) = \begin{cases} 
\frac{e^{f_i^T f_n}}{\sum_{j=1}^N e^{f_i^T f_j}} & n \in [1, N] \\
1 & n = 0 
\end{cases}
\]

where \(1 \leq n \leq N\) indicates the candidate is associated to one of the \(N\) instances and \(n = 0\) means the candidate is treated as a new identity. \(f_i\) and \(f_j\) (\(j \in [1, N]\)) denote the feature embedding of the candidate and the \(N\) pre-identified instances, respectively. The cross-entropy loss is used here in a way of multi-class classification.

The overall training loss function used is a combination of the Mask R-CNN losses and the tracking loss. During inference, MaskTrack R-CNN maintains a memory to store the feature vectors of existing instances. For more details (e.g., memory update, inference strategy, model setup), please refer to [49].

4.2. Temporal Feature Calibration

One of the keys to tackling occlusion is to complement the missing object cues. In a video that has a temporal dimension, a mild assumption is that usually, the missing object cues in the current frame may have appeared in adjacent frames. Hence, it is natural to leverage adjacent frames

Figure 6. The pipeline of temporal feature calibration, which can be inserted into different video instance segmentation models by changing the prediction head. We verify this flexibility using MaskTrack R-CNN and SipMask in our experiments.
Table 2. Quantitative comparison with state-of-the-art methods on the OVIS validation and test set.

| Methods              | OVIS validation set | OVIS test set |
|----------------------|---------------------|---------------|
|                      | AP  | AP_{50} | AP_{75} | AR_{1} | AR_{10} | AP  | AP_{50} | AP_{75} | AR_{1} | AR_{10} |
| FEELVOS [38]         | 9.6 | 22.3    | 7.6     | 7.4    | 14.8    | 11.5| 23.7 | 8.4    | 9.2    | 16.3    |
| IoUTracker+ [49]     | 7.3 | 17.9    | 5.5     | 6.1    | 15.1    | 9.5 | 18.8 | 10.0   | 6.6    | 16.5    |
| MaskTrack R-CNN [49] | 10.9| 26.0    | 8.1     | 8.3    | 15.2    | 12.6| 27.3 | 10.7   | 8.3    | 16.6    |
| SipMask [4]          | 13.8| 25.4    | 7.8     | 7.9    | 15.8    | 12.1| 24.9 | 11.1   | 8.3    | 17.0    |
| STEm-Seg [1]         | 13.3| 32.1    | 11.9    | 9.1    | 14.8    | 14.4| 30.0 | 13.0   | 10.1   | 20.6    |
| CSipMask (ours)      | 13.9| 30.7    | 11.9    | 9.4    | 19.4    | 15.0| 30.4 | 13.4   | 9.7    | 20.8    |

Table 3. Quantitative comparison with state-of-the-art methods on the YouTube-VIS validation set.

| Methods                   | YouTube-VIS validation set |                        |
|---------------------------|-----------------------------|-------------------------|
|                           | AP  | AP_{50} | AP_{75} | AR_{1} | AR_{10} | AP  | AP_{50} | AP_{75} | AR_{1} | AR_{10} |
| FEELVOS [38]              | 26.9| 42.0    | 29.7    | 29.9   | 33.4    | 20.0| 35.0 | 27.8   | 31.3   |
| IoUTracker+ [49]          | 23.6| 39.2    | 25.5    | 26.2   | 30.9    | 32.4| 53.0 | 33.3   | 38.9   |
| OSMN [50]                 | 27.5| 45.1    | 29.1    | 28.6   | 33.1    | 31.2| 50.7 | 33.5   | 37.1   |
| DeepSORT [43]             | 26.1| 42.9    | 26.1    | 27.8   | 31.3    | 30.3| 51.1 | 32.6   | 35.5   |
| MaskTrack R-CNN [49]      | 30.3| 51.1    | 32.6    | 31.0   | 35.5    | 32.5| 53.0 | 33.3   | 38.9   |
| SipMask [4]               | 32.5| 53.0    | 33.3    | 33.5   | 38.9    | 30.6| 50.7 | 33.5   | 37.1   |
| STEm-Seg [1]              | 32.3| 52.3    | 34.4    | 32.8   | 37.6    | 32.7| 54.3 | 33.4   | 37.6   |

Table 4. Quantitative comparison with state-of-the-art methods on the YouTube-VIS validation set.

5. Experiments

The experiments are mainly focused on two aspects, including 1) a comprehensive evaluation of 5 existing video instance segmentation algorithms to benchmark the baseline performance of our OVIS dataset, and 2) a performance comparison between our method (CMaskTrack R-CNN and CSipMask) and state-of-the-art algorithms in both OVIS and YouTube-VIS.

5.1. Dataset, Metric and Implementation Details

The YouTube-VIS dataset [49] has 2,238 training videos, 302 validation videos, and 343 test videos. We train our model on the training set and report the performance on the validation set. On the newly collected OVIS dataset, the whole dataset is randomly divided into 607 training videos, 302 validation videos, and 343 test videos. Following previous methods [49], we use average precision (AP) at different intersection-over-union (IoU) thresholds and average recall (AR) as the evaluation metrics. The mean value of APs is also employed.

We adopt ResNet-50-FPN [14] as backbone for all our experiments. The model is initialized by Mask R-CNN which is pre-trained on MS-COCO [28]. Three convolution layers of kernel size 3 × 3 are used in the module for sample a reference frame \( F_r \) from the same video. In order to ensure that the reference frame has a strong spatial correspondence with the query frame, the sampling is only done locally within \( \epsilon_{train} = 5 \) frames. Since the temporal feature calibration is differentiable, it can be trained end-to-end by the original detection and segmentation loss. When inference, all frames adjacent to the query frame within the range \( \epsilon_{test} = 3 \) are taken as reference frames. We linearly fuse the classification confidences, regression bounding box coordinates, and segmentation masks obtained from each reference frame and output the final results for the query frame.

In the experiments, we denote our method as CMaskTrack R-CNN and CSipMask, when Calibrating MaskTrack R-CNN [49] models and Calibrating SipMask [4] models, respectively.
temporal feature calibration. The training epoch is set to 12, and the initial learning rate is set to 0.005 and decays with a factor of 10 at epoch 8 and 11. All frames are resized to 640 \times 360 during both training and inference.

5.2. Comparison with State-of-the-art

On the OVIS dataset, we first produce the performance of several state-of-the-art algorithms whose code is publicly available, including mask propagation methods (e.g., FEELVOS [38]), track-by-detect methods (e.g., IoUTracker+ [49]), and recently proposed end-to-end methods (e.g., MaskTrack R-CNN [49], SipMask [4], and STEm-Seg [1]).

As presented in Table 2 and Table 3, all those methods encounter a performance degradation of at least 50% on OVIS compared with that on YouTube-VIS. For example, the AP of SipMask [4] decreases from 32.5 to 12.1 and that of STEm-Seg [1] decreases from 30.6 to 14.4. It firmly suggests that further attention should be paid to video instance segmentation in the real world where occlusions extensively happen.

Benefiting from 3D convolutional layers and the bottom-up architecture, STEm-Seg surpasses other methods on OVIS and reports an AP of 14.4. Our interpretation is that 3D convolution is conducive to sensing temporal context, and the bottom-up architecture avoids the detection process which is difficult in occluded scenes.

By leveraging the feature calibration module, the performance on OVIS is significantly improved. Our CMaskTrack R-CNN leads to an AP improvement of 2.6 over MaskTrack R-CNN (12.6 vs. 15.2), and our CSipMask leads to an AP improvement of 2.9 over SipMask (12.1 vs. 15.0). Both achievements are superior to that of STEm-Seg, by a margin of 0.8 and 0.6 in terms of AP, respectively.

Some evaluation examples of CMaskTrack R-CNN on OVIS are given in Fig. 7, including 4 successful cases (a)-(d) and 2 failure cases (e)-(f). In (a), our model successfully tracks the bear in the yellow mask, which is partially occluded by another object, i.e., the bear in the purple mask, and the background, i.e., the tree. In (c), we present a crowded scene where almost all the ducks are correctly detected and tracked, with only a missing detection on the leftmost duck in the 2nd frame. However, it is surprising to see that the duck is re-tracked in later frames, which reveal that the temporal cues are well captured by our model. In (d), the car in the yellow mask first blocks the car in the red mask entirely in the 2nd frame, then is entirely blocked by the car in the purple mask in the 4th frame. Even in this extreme case, all the cars are well tracked. In (e), two persons and two bicycles heavily overlap with each other. Our

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1 The performance of some methods is also being produced by the authors of the corresponding papers, which will be updated afterward.
model fails to track the person and segment the bicycle. In (f), although humans could sense that there are two persons with hat in the bottom, our model cannot detect and track them because the appeared visual cues are inadequate.

We further evaluate the proposed CMaskTrack R-CNN and CSipMask on the YouTube-VIS dataset. As shown in Table 3, CMaskTrack R-CNN and CSipMask surpass the corresponding baseline by 1.8 and 2.5 in terms of AP, respectively, which demonstrates the flexibility and the generalization power of the proposed feature calibration module. Moreover, our methods also beat other representative methods by a larger margin, including DeepSORT [43], STEm-Seg [1], etc. In [2], Gedas et al. propose MaskProp by replacing the bounding-box level tracking in MaskTrack R-CNN by a novel mask propagation mechanism. By using a larger backbone (STSN [3]-ResNeXt-101-64x4d [45]), a better detection network (HybridTask Cascade Network [5]), higher resolution inputs for segmentation network, and more training iterations, it reports a much higher AP of 46.6 on YouTube-VIS. We believe that our module is also pluggable to this strong baseline and better performance could be achieved. Meanwhile, it is also interesting to evaluate the performance of MaskProp on OVIS after its code is released.

5.3. Discussions

Ablation Study. We study the temporal feature calibration module with a few alternatives. The first option is a naive combination, which sums up the feature of the query frame and the reference frame without any feature alignment. The second option is to replace the correlation operation in our module by calculating the element-wise difference between feature maps, which is similar to the operation used in [2]. We denote the two options as “Add” and “Difference”, respectively and our module as “Calibration” in Fig. 8.

As we can see, with both models, “Add” achieves the poorest performance, which shows that a kind of feature calibration between different frames is necessary and beneficial to an accurate prediction of video instance segmentation. Meanwhile, “Calibration” consistently outperforms “Difference” with a decent performance boost. For example, “Calibration” achieves an AP of 15.2, an improvement of 0.8 over “Difference” with MaskTrack R-CNN as the base model, and achieves an AP of 13.9, an improvement of 0.9 over “Difference” with SipMask as the base model. We argue that the correlation operation is able to provide a richer context for feature calibration because it calculates the similarity between the query position and its neighboring positions, while the element-wise difference only considers the difference between the same positions.

Oracle Results. In addition, we conduct an experiment to explore the upper bounds of our method on OVIS by replacing the image level predictions with ground-truth. Specifically, we use ground-truth bounding boxes, masks and categories to replace the predictions by CMaskTrack R-CNN, track those ground-truth bounding boxes with the tracking branch, then obtain final instances. By doing so, we achieve an AP of 58.4 and an AR_{10} of 66.1, which demonstrates that the image level prediction is critical for the performance of occluded video instance segmentation.

6. Conclusions

In this work, we target video instance segmentation in occluded scenes, and accordingly contribute a large-scale dataset called OVIS. OVIS consists of 296k high-quality instance masks of 5,223 heavily occluded instances. While being the second benchmark dataset after YouTube-VIS, OVIS is designed to examine the ability of current video understanding systems in terms of handling object occlusions. A general conclusion comes to that the baseline performance on OVIS is far below that on YouTube-VIS, which suggests that more effort should be devoted in the future to tackling object occlusions or de-occluding objects [51]. We also explore ways about leveraging temporal context cues to alleviate the occlusion matter, and report an AP of 15.2 on OVIS and 35.0 on YouTube-VIS, a remarkable gain over the state-of-the-art algorithms.

In the future, we are interested in formalizing the experimental track of OVIS for video object segmentation, either in an unsupervised, semi-supervised, or interactive setting. It is also of paramount importance to extend OVIS to video panoptic segmentation [20]. As we can see from Fig. 2, a type of occlusion is caused by the background, therefore in this case, heavy occlusions will also affect the prediction of background stuff. At last, synthetic occluded data [32] requires further exploration. We believe the OVIS dataset will trigger more research in understanding videos in complex and diverse scenes.
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