Tracking Instances as Queries

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Abstract

Recently, query based deep networks catch lots of attention owing to their end-to-end pipeline and competitive results on several fundamental computer vision tasks, such as object detection [18], semantic segmentation [24], and instance segmentation [6]. However, how to establish a query based video instance segmentation (VIS) framework with elegant architecture and strong performance remains to be settled. In this paper, we present QueryTrack (i.e., tracking instances as queries), a unified query based VIS framework fully leveraging the intrinsic one-to-one correspondence between instances and queries in QueryInst [6]. The proposed method obtains 52.7 / 52.3 \( \text{AP} \) on YouTube-VIS-2019 / 2021 datasets, which wins the 2\textsuperscript{nd} place in the YouTube-VIS Challenge at CVPR 2021 with a single online end-to-end model, single scale testing & modest amount of training data. We also provide QueryTrack-ResNet-50 baseline results on YouTube-VIS-2021 \textit{val} set as references for the VIS community.

1. Introduction

Video Instance Segmentation (VIS) [21] is an emerging computer vision task and get rapid development since it was proposed. This task extends the traditional instance segmentation to the temporal domain and requires detecting, classifying, segmenting, and tracking visual instances simultaneously in the given videos. Similar to other video based tasks like Video Object Segmentation [12, 25] and Video Object Detection [14], video instance segmentation provides a natural understanding of video scenes. Achieving accurate and robust video instance segmentation in real-world scenarios can greatly promote the development of video analysis.

Given the inherent relationship between video instance segmentation and instance segmentation, prevalent video instance segmentation methods [1, 2, 3, 7, 21, 22] prefer utilizing off-the-shelf instance segmentation approaches with various modules for inter-frame feature aggregation and temporal instances association. As a result, modern video instance segmentation methods usually use the one-to-many matching between predictions and ground truth instances, thus the inference process is sensitive to manual-designed post-process operators and far from end-to-end. Moreover, to associate instances across video frames, current VIS methods [3, 21] require heuristic association approach and bring lots of hyper-parameters.

To remedy these issues, we propose a unified end-to-end query based video instance segmentation method, termed as QueryTrack (i.e., tracking instances as queries). The proposed method is built upon the state-of-the-art query based instance segmentation method QueryInst [6], which exploits the intrinsic one-to-one correspondence in object queries across different stages, and one-to-one correspondence between mask RoI features and object queries in the same stage. Moreover, an elaborate tracking head is introduced to fully leverage the potential of instance queries for the temporal association. With the one-to-one correspondence between instances and queries, QueryTrack enjoys a unified end-to-end paradigm. Moreover, the well-designed tracking head greatly reduces the number of hyper-parameters.

The proposed QueryTrack is evaluated on the YouTube-VIS Challenge 2021, which achieves 52.3\% \( \text{AP} \) on the \textit{test} set and the 2\textsuperscript{nd} place on the final leaderboard. We also conduct experiments on YouTube-VIS 2019 [21] dataset, where QueryTrack outperforms a deal of previous state-of-the-art methods. To facilitate future research, we also report results of QueryInst powered by ResNet-50 [9] backbone on YouTube-VIS-2021 \textit{val} set\textsuperscript{1}. With a simple framework and

\textsuperscript{1}It is common sense that the widely used YouTube-VIS 2019 benchmark usually suffers from high variances [22]. The YouTube-VIS 2021 benchmark is an augmented version of the 2019 version that producing much more reliable results (we observe \( \sim 0.5 \) \( \text{AP} \) noise for a wide range of VIS models). We encourage the community to evaluate VIS methods

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competitive performances, we hope QueryTrack can serve as a strong baseline for video instance segmentation.

2. Method

In this section, we explicate the architecture design of QueryTrack in detail. Fig 1 gives an overall illustration of the proposed methods.

2.1. Query Based Instance Segmentation

As aforementioned, QueryTrack is built on the top of QueryLst [6], the well-designed query based instance segmentation framework. The overall object detection and instance segmentation pipelines are summarized as follows.

**Object Detection.** The object detection pipeline can be formulated as:

\[
\begin{aligned}
x_t^{\text{box}} &\leftarrow \mathcal{P}^{\text{box}} (x_{FPN}^{\text{FPN}}, b_{t-1}), \\
q_{t-1}^* &\leftarrow \text{MSA}_t (q_{t-1}), \\
x_t^{\text{box}}, q_t &\leftarrow \text{DynConv}_t^{\text{box}} (x_t^{\text{box}}, q_{t-1}), \\
b_t &\leftarrow B_t (x_t^{\text{box}}),
\end{aligned}
\]

where \( q \in \mathbb{R}^{N \times d} \) indicates the instance query while \( N \) and \( d \) denote the total number and dimension of instance query, respectively. For bounding box prediction, at stage \( t \), a pooling operator \( \mathcal{P}^{\text{box}} \) extracts the current stage bounding box feature \( x_t^{\text{box}} \) from FPN feature \( x_{FPN} \) under the guidance of previous stage bounding box prediction \( b_{t-1} \). Meanwhile, a multi-head self-attention module \( \text{MSA}_t \) is applied to the input query \( q_{t-1} \) to get the transformed query \( q_{t-1}^* \). Then, a box dynamic convolution module \( \text{DynConv}_t^{\text{box}} \) takes \( x_t^{\text{box}} \) and \( q_{t-1}^* \) as inputs and enhances the \( x_t^{\text{box}} \) by reading \( q_{t-1}^* \) and generates \( q_t \) for the next stage. Finally, the enhanced bounding box feature \( x_t^{\text{box}} \) are fed into the box prediction branch \( B_t \) for current stage bounding box prediction \( b_t \).

**Instance Segmentation.** For instance mask prediction, a region-wise pooling operator \( \mathcal{P}^{\text{mask}} \) extracts the current stage mask feature \( x_t^{\text{mask}} \) from FPN feature \( x_{FPN} \), under the guidance of current stage bounding box prediction \( x_t^{\text{box}} \). A mask dynamic convolution module \( \text{DynConv}_t^{\text{mask}} \) enhances the original mask feature \( x_t^{\text{mask}} \) and generates \( x_t^{\text{mask}*} \). Afterwards, current stage mask head \( \mathcal{M}_t \) generates the instance level mask prediction \( m_t \) by a stack of convolutional layers. The overall procedure of instance mask generation can be formulated as follows:

\[
\begin{aligned}
x_t^{\text{mask}} &\leftarrow \mathcal{P}^{\text{mask}} (x_{FPN}^{\text{FPN}}, b_t), \\
x_t^{\text{mask}*} &\leftarrow \text{DynConv}_t^{\text{mask}} (x_t^{\text{mask}}, q_{t-1}^*), \\
m_t &\leftarrow \mathcal{M}_t (x_t^{\text{mask}*}),
\end{aligned}
\]

**Bipartite Matching.** Following [5, 6], we adapt Hungarian matching to build the one-to-one correspondences between predictions and ground truth instances. The matching cost of Hungarian matcher is defined as:

\[
\mathcal{L}_{\text{Hungarian}} = \lambda_{\text{cls}} \cdot \mathcal{L}_{\text{cls}} + \lambda_{L1} \cdot \mathcal{L}_{L1} + \lambda_{\text{giou}} \cdot \mathcal{L}_{\text{giou}} \tag{3}
\]

where \( \mathcal{L}_{\text{cls}}, \mathcal{L}_{L1} \) and \( \mathcal{L}_{\text{giou}} \) indicate the focal loss, L1 loss and generalized IoU loss, respectively. \( \lambda_{\text{cls}}, \lambda_{L1} \) and \( \lambda_{\text{giou}} \) are set as the same as [6].

2.2. Contrastive Tracking Head

**Dynamic Instance Embedding.** To perform temporal instances association, we first embed all instances to a latent space by a dynamic instance embedding head. Specifically, the embedding process can be formulated as follows:

\[
\begin{aligned}
x_t^{\text{track}} &\leftarrow \mathcal{P}^{\text{track}} (x_{FPN}^{\text{FPN}}, b_t), \\
x_t^{\text{track}*} &\leftarrow \text{DynConv}_t^{\text{track}} (x_t^{\text{track}}, q_{t-1}^*), \\
e_t &\leftarrow \mathcal{T}_t (x_t^{\text{track}*}),
\end{aligned}
\]

Similar to mask prediction, firstly, a region-wise pooling operator extracts instance feature \( x_t^{\text{track}} \), a track dynamic convolution module \( \text{DynConv}_t^{\text{track}} \) enhances the instance feature under the guidance of instance query. Then, a linear projection module \( \mathcal{T}_t \) projects \( x_t^{\text{track}*} \) to a latent space and generates instance embedding \( e_t \).

**Contrastive Learning.** Following [21, 22], we take a pair of frames as inputs to train the tracking head. During training, the frame pairs are randomly sampled from a training video. One of the frames is picked as the key frame, which is fed to the instance segmentation network to get a set of instance predictions. While the other frame is treated as a reference frame, which aims to provide ground truth identities and reference instance embeddings. Assuming there is a detected instances \( I_t \) at the key frame, and there are \( N \) already identified instances in the reference frame. It’s clear that there is at most one existing identity in reference frame can be assigned to the detected instances. The probability of assigning label \( n \) to detected instance \( I_t \) can be formulated as:

\[
p_t(n) = \left\{ \begin{array}{ll}
\frac{\exp(e_t^\top e_n)}{1 + \sum_{j=1}^N \exp(e_t^\top e_j)} & \text{if } n \in [1, N], \\
1 & \text{otherwise},
\end{array} \right.
\]

where \( e_t \) and \( e_j \) denote the instance embedding of \( I_t \) and \( n \) instance embeddings in reference frame. Different from [21], which introduces a cross-entropy loss function to optimize the tracking head, QueryTrack adapts a contrastive focal loss to reduce the conflict of multi-task learning. Specifically, the loss function for tracking heads is defined as fol-
low:
\[ p_t^*(n) = \begin{cases} 
  p_t(n) & \text{if } I_t = I_n, \\
  1 - p_t(n) & \text{otherwise},
\end{cases} \]
\[ L_{track} = -\alpha_e(1 - p_t^*(n))^\gamma \log(p_t^*(n)), \tag{7} \]

2.3. Online Instance Association

Tracking instances across video frames purely based on the instance embedding is non-trivial as appearance similarity might be confused by instance deformation, occlusion and background change. Similar to \cite{21, 23}, QueryTrack leverages several tracking clues such as spatial similarity, detection confidence and category consistency to perform better instance association. Specifically, assume there are \( M \) candidate instances and \( N \) already identified instances, the matching factor between one candidate instance \( m \in [1, M] \) one identified instance \( n \in [1, N] \) can be formulated as:
\[ F_{m,n} = S_{m,n} \cdot \frac{1 + \text{IoU}(b_m, b_n)}{2} \cdot \frac{1 + \pi_m}{2} \cdot \delta(c_m, c_n) \tag{8} \]
where \( \text{IoU}(b_m, b_n) \) indicates the bounding box \( \text{IoU} \) (intersection over union) between candidate instance \( m \) and identified instance \( n \), \( \pi_m \) indicates the detection confidence of candidate instance \( m \), and \( \delta(c_m, c_n) \) is an indicator function which gets 1 when the two instances have the same category predictions (\( c_m = c_n \)) and gets 0 otherwise. \( S_{m,n} \) indicates the normalized appearance similarity between two instances. Specifically, the similarity is normalized by a bidirectional softmax \cite{17}, the computation process can be formulated as follows:
\[ S_{m,n} = \left( \frac{\exp(e_m^t e_n)}{\sum_{n=1}^{N} \exp(e_m^t e_n)} + \frac{\exp(e_n^t e_m)}{\sum_{k=1}^{M} \exp(e_k^t e_n)} \right) / 2 \tag{9} \]

3. Experiments

3.1. Datasets

We mainly evaluate QueryTrack on YouTube-VIS 2021 dataset, which is used for YouTube-VIS Challenge 2021. Besides, we also report the system level comparisons between QueryTrack and several state-of-the-art methods on YouTube-VIS 2019 dataset.

3.2. Implementation Details

Training Setup. The basic training setup of QueryTrack is mainly following the original QueryInst \cite{6}. Specifically, the R-CNN head of QueryTrack contains 6 stages and the total number of queries is set to 300. We adopt the recently proposed transformer network \cite{4, 15} as the backbone, and use COCO pre-trained weights for parameter initialization. The training process on YouTube-VIS consists of 12 epochs in total. For each iter, the batch size is set to 32 and we use AdamW optimizer with an initial learning rate of \( 1.25 \times 10^{-5} \). The learning rate decreases by 10 at 9th and 11th epoch. Data augmentation includes random flip, multi-scale input, and random crop. Input images are resized such that the shorter side is at least 320 and at most 800, while the other side no longer than 1333. QueryTrack only exploit modest amount of training data. Unlike other methods in VIS competitions, we do not use Open-Iamg data \cite{11} for better performance.

Inference. Since most of the videos in both YouTube-VIS 2019 \cite{21} and YouTube-VIS 2021 have no more than 10 video instances, during inference we only extract the top 10 instance predictions as valid candidates. The instance masks are generated from the final stage mask head, and the final stage tracking head is used to associate temporal instances. All input images during the inference stage are resized to have their shorter side being 640 and their longer side no longer than 1333.

3.3. YouTube-VIS-2021 Val Set Baseline

We report QueryInst-ResNet-50 baseline results on the YouTube-VIS-2021 val set as references for the VIS community. The training setting keeps the same as described in Sec. 3.2, except the number of queries is 100 (which will degenerate the performance), and we don’t use crop augmentation. During inference, the input video frame resolution is \( 360 \times 640 \) (i.e., 360p).
The results are shown in Tab. 1. We demonstrate that QueryTrack with ResNet-50 backbone can serve as a very strong baseline for video instance segmentation future research.

### 3.4. Main Results

Tab. 2 shows the results in the final leaderboard of YouTube-VIS Challenge 2021. With a single model, our QueryTrack achieves 52.3 AP in the test set of YouTube-VIS 2021, and wins the 2\textsuperscript{nd} place in YouTube-VIS Challenge 2021.

Tab. 3 shows the system level comparisons between QueryTrack and state-of-the-art video instance segmentation methods. As shown in the table, QueryTrack outperforms previous state-of-the-art video instance segmentation methods by a large margin.

### 4. Conclusion

We present QueryTrack, a unified query based end-to-end framework for the challenging video instance segmentation task. We build our method upon the state-of-the-art instance segmentation model QueryInst [6] with an elaborate tracking head. Despite the simple & concise framework, QueryTrack produces very strong results and achieves the 2\textsuperscript{nd} place in the YouTube-VIS Challenge 2021. We also provide some competitive baselines on YouTube-VIS-2021 val set to facilitate future research, and we encourage the community to evaluate VIS models on YouTube-VIS-2021 dataset for better reproducibilities.

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