MOTR: End-to-End Multiple-Object Tracking with TRansformer

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Track queries

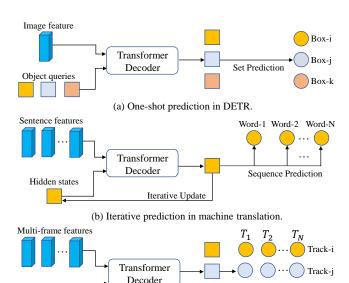
Abstract

The key challenge in multiple-object tracking task is temporal modeling of the object under track. Existing tracking-by-detection methods adopt simple heuristics, such as spatial or appearance similarity. Such methods, in spite of their commonality, are overly simple and lack the ability to learn temporal variations from data in an end-to-end manner.

In this paper, we present MOTR, a fully end-to-end multipleobject tracking framework. It learns to model the long-range temporal variation of the objects. It performs temporal association implicitly and avoids previous explicit heuristics. Built upon DETR (Carion et al. 2020), MOTR introduces the concept of "track query". Each track query models the entire track of an object. It is transferred and updated frame-byframe to perform iterative predictions in a seamless manner. Tracklet-aware label assignment is proposed for one-to-one assignment between track queries and object tracks. Temporal aggregation network together with collective average loss is further proposed to enhance the long-range temporal relation. Experimental results show that MOTR achieves competitive performance and can serve as a strong Transformerbased baseline for future research. Code is available at https: //github.com/megvii-model/MOTR.

1 Introduction

Multiple-object tracking (MOT) is a class of visual object detection, where the task is not only localize all targets in each frame but also predict the moving trajectories of those objects in video sequences (Wojke et al. 2017; Bergmann et al. 2019). Most existing methods model the temporal motion, regarding to the appearance and position variances, in a separate manner. Usually, appearance variance is measured by the Re-ID similarity (Wang et al. 2020; Zhang et al. 2021) while the position variance is modeled via heuristic like Kalman Filtering (Bewley et al. 2016), making the learning of temporal motion not end-to-end. Besides, these methods, mainly following the tracking-by-detection paradigm, tend to require post-processes like IoU-matching (Bochinski et al. 2017) to explicitly associate the bounding box sequences as tracks, also making the whole pipeline not endto-end. In this paper, we aim to introduce a fully end-to-end



(c) Iterative prediction of box sequences in MOTR.

Set of Sequence Prediction

Iterative Update

Figure 1: (a) DETR achieves end-to-end detection by interacting object queries with image features and performs one-to-one assignment between the updated queries and objects. (b) Machine translation approaches perform iterative predictions by recurrently updating the hidden states. (c) Inspired by both (a) and (b), MOTR performs set of sequence prediction by updating the track queries. Each track query represents a track. Best viewed the figure in color.

MOT framework that jointly learns the temporal variances of both appearance and position, removing explicit associations, such as IoU and Re-ID matching.

Recently, DETR (Carion et al. 2020; Zhu et al. 2020) was proposed for end-to-end object detection. It formulates the object detection as a set prediction problem. As shown in Fig. 1(a), object queries, served as a decoupled representation of objects, are input to the Transformer decoder and interacted with the image feature to update its representation. Bipartite matching is further adopted to achieve one-to-one assignment between the object queries and ground-truths (GTs), eliminating post-processes like NMS. Different from object detection, MOT can be regraded as a sequence prediction problem. How to perform sequence prediction on the

^{*}Equal contribution. This work is supported by The National Key Research and Development Program of China (No.2017YFA0700800) and Beijing Academy of Artificial Intelligence (BAAI).

end-to-end DETR system is an opening question.

In the field of machine translation, predicting sequence in an iterative manner is popular (Sutskever et al. 2014; Vaswani et al. 2017). Usually, a hidden state is introduced to encode context and iteratively interacts with sentence features for sequence prediction of translated words (see the Fig. 1(b)). Inspired by these advances in machine translation, we intuitively regard MOT as a problem of set of sequence prediction since MOT requires a set of object sequences. Each sequence corresponds to an object trajectory. Technically, we extend object query in DETR to track query for predicting object sequences. Track queries are served as the hidden states of object tracks. The representations of track queries are updated in Transformer decoder and used to predict the object trajectory in an iterative manner (see the Fig. 1(c)). Specifically, track queries are updated through self-attention and cross-attention by multi-frame features. The updated track queries are further used to predict the bounding boxes. All predictions of one track query naturally form the track of one object.

To achieve the goal above, there are two main problems: 1) how to track one object by one track query; 2) how to deal with new-born and dead objects. For the first problem, we technically introduce tracklet-aware label assignment (TALA) during training. It means that predictions of one track query are supervised by bounding box sequences with the same identity. For second problem, we employ a track query set of dynamic length. Queries of new-born objects are merged into the set while queries of dead objects are removed. We term such process as entrance and exit mechanism. In this way, explicit track associations like IoU matching are no longer required during inference. Moreover, with the iterative update of track query, temporal variances regarding to both appearance and position can be learned implicitly. To enhance the learning of long-range temporal motion, we further propose collective average loss (CAL) and temporal aggregation network (TAN). With the CAL, MOTR takes video clips as input during training. The parameters of MOTR are updated based on the overall loss calculated for the whole video clip. TAN introduces a shortcut for track query to aggregate historical information from its previous states via multi-head attention.

MOTR is a simple online tracker. It is easy to developed based on DETR with small modification on label assignment. It is a truly end-to-end MOT framework, requiring no post-processes, such as the track NMS or IoU matching employed in our concurrent works, TransTrack (Sun et al. 2020) and TrackFormer (Meinhardt et al. 2021). Experimental results on MOT16 and MOT17 datasets show that MOTR achieves promising performance.

To summarize, our contributions are listed as below:

- We present a fully end-to-end MOT framework, termed MOTR based on DETR. MOTR can implicitly learn the appearance and position variances in a joint manner.
- We formulates MOT as a problem of *set of sequence prediction*. To solve it, track query is extended as the hidden state for iterative update and prediction.
- TALA is proposed for one-to-one assignment between

- track queries and objects. An entrance and exit mechanism is introduced to deal with new-born and dead tracks.
- CAL and TAN are further proposed to enhance the learning of long-range temporal motion.

2 Related Work

Transformer-based Architectures: Transformer (Vaswani et al. 2017) was first introduced to aggregate information from the entire input sequence for machine translation. It mainly involves self-attention and cross-attention mechanisms. Since that, it was gradually introduced to many fields, such as speech processing (Li et al. 2019; Chang et al. 2020) and computer vision (Wang et al. 2018; Camgoz et al. 2020). Recently, DETR (Carion et al. 2020) combined convolutional neural network (CNN), Transformer and bipartite matching to perform end-to-end object detection. To achieve the fast convergence, Deformable DETR (Zhu et al. 2020) introduced deformable attention module into Transformer encoder and Transformer decoder. ViT (Dosovitskiy et al. 2021) built a pure Transformer architecture for image classification. The image is divided into 16x16 patches, which serve as the input of Transformer-based network after linear projection. Further, Swin Transformer (Liu et al. 2021) proposed shifted windowing scheme to perform self-attention within local windows, bringing greater efficiency.

Multiple-Object Tracking: Dominant MOT methods mainly followed the tracking-by-detection paradigm (Bewley et al. 2016; Leal-Taixé et al. 2016; Schulter et al. 2017; Sharma et al. 2018; Wojke et al. 2017). These approaches usually first employ object detectors to localize objects in each frame and then perform track association between adjacent frames to generate the tracking results. SORT (Bewley et al. 2016) conducted track association by combining Kalman Filter (Welch et al. 1995) and Hungarian algorithm (Kuhn 1955). DeepSORT (Wojke et al. 2017) and Tracktor (Bergmann et al. 2019) introduced an extra cosine distance and compute the appearance similarity for track association. Track-RCNN (Shuai et al. 2020), JDE (Wang et al. 2020) and FairMOT (Zhang et al. 2021) further added a Re-ID branch on top of object detector in a joint training framework, incorporating object detection and Re-ID feature learning. Our concurrent works, TransTrack (Sun et al. 2020) and TrackFormer (Meinhardt et al. 2021) also develop Transformer-based frameworks for MOT. For direct comparison with them, please refer to Sec. 3.7.

Iterative Sequence Prediction: Predicting sequence via sequence-to-sequence (seq2seq) together with encoder-decoder architecture is popular in machine translation (Sutskever et al. 2014; Vaswani et al. 2017) and text recognition (Shi et al. 2016). In such seq2seq framework, the input is encoded into intermediate representation by the encoder network. Then, a hidden state with task-specific context information, is introduced and iteratively interacted with the intermediate representation to generate target sequence through the decoder network. The iterative decode process contains several iterations. In each iteration, the hidden state decodes one element of the target sequence.

3 Method

3.1 Query in Object Detection

DETR (Carion et al. 2020) introduced object queries, a fixed-length set of learnable embeddings, to represent objects. Object queries are input to the Transformer decoder and interacted with image feature extracted from Transformer encoder to update their representation. Bipartite matching is further adopted to achieve one-to-one assignment between the updated object queries and ground-truths (GTs). Here, we simply write the object query as "detect query" to specify the query used for object detection.

3.2 Detect Query and Track Query

When adapting DETR framework from object detection to MOT, two main problem arise: 1) how to track one object by one track query; 2) how to adaptively track objects since each frame may introduce new-born and dead objects. In this paper, we extended the track queries from detect queries. Track queries can serve as hidden states to perform iterative tracking prediction. As shown in Fig. 2, the track query set is empty at initial frame T_1 . The fixed-length detect queries (yellow boxes) in DETR are used to detect new-born objects (such as "3" at T_i). Detect queries assigned to new-born objects are updated and merged into the track query set at next frame. Track query set is of adaptive length and dynamically updated. Track queries assigned to dead objects ("2" at T_k) are removed from track query set.

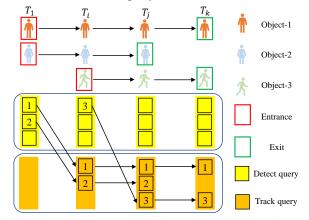


Figure 2: The update process of detect (object) queries and track queries under some typical MOT cases.

3.3 Tracklet-Aware Label Assignment

In DETR, one detect (object) query may be assigned to any one object in image since the label assignment is determined by performing bipartite matching between all detect queries and GTs. While in MOTR, detect queries are only used to detect the new-born objects and track queries predict these tracked objects. Here, we introduce the tracklet-aware label assignment (TALA) to achieve this goal.

Generally, TALA consists of two strategies. For detect queries, we modify the assignment strategy in DETR as **new-born-only**, where bipartite matching is conducted between the detect queries and the GTs of new-born objects.

For track queries, we design an **target-consistent** assignment strategy. Track queries are excluded from the bipartite matching and follow the same assignment of previous frames. Formally, we denote the predictions and GTs for frame T_i as $Y_i = \{Y_{tr}^i, Y_{det}^i\}$ and $\hat{Y}_i = \{\hat{Y}_{tr}^i, \hat{Y}_{det}^i\}$, respectively. Here, Y_{tr}^i, Y_{det}^i are the predictions of track queries and detect queries. \hat{Y}_{tr}^i and \hat{Y}_{det}^i are the corresponding GTs. The label assignment results between the predictions and GTs for track queries and detect queries can be written as $\omega_i = \{\omega_{tr}^i, \omega_{det}^i\}$, and can be formulated as:

$$\hat{\omega}_{det}^{i} = \underset{\omega_{det}^{i} \in \Omega_{i}}{arg \min} \mathcal{L}(Y_{det}^{i}|_{\omega_{det}^{i}}, \hat{Y}_{det}^{i}))$$
(1)

$$\omega_{tr}^{i} = \begin{cases} \emptyset & i = 1 \\ \omega_{tr}^{i-1} \cup \omega_{det}^{i-1} & 2 \leq i \leq N \end{cases}$$
 (2)

Here, N is the length of video sequence and $\mathcal L$ is the pairwise matching cost defined in DETR. At the initial frame T_1 , ω^1_{tr} is empty since no objects are tracked previously while ω^1_{det} is determined by the bipartite matching between \hat{Y}^1_{det} and Y^1_{det} . At any frame $T_i|_{2\leq i\leq N}$, ω^i_{det} is still determined by the bipartite matching between \hat{Y}^i_{det} and Y^i_{det} . ω^i_{tr} is generated by merging ω^{i-1}_{tr} and ω^{i-1}_{det} . It means that we follow the same assignment of frame T_{i-1} for tracked objects. While for the new-born objects in T_{i-1} frame, we merge the corresponding detect queries into the track query set of T_i . The detailed process that merges the detect queries into track query set will be described in Sec. 3.5.

TALA strategy is simple and effective thanks to the powerful attention mechanism in Transformer. In practice, detect queries and track queries are first concatenated together and input to the Transformer decoder to update their representation. In Transformer decoder, the concatenated queries will interact with each other by self-attention and suppress those detect queries that detect the tracked objects. It is similar to the duplicate removal in DETR where duplicate boxes are suppressed with low scores.

3.4 MOTR Architecture

The overall architecture of MOTR is shown in Fig. 3. Video sequences are input to the convolutional neural network (CNN) (e.g. ResNet-50 (He et al. 2016)) and Transformer encoder in DETR (Carion et al. 2020) to extract the basic feature list $f = \{f_1, f_2, \dots, f_N\}$. For the T_1 frame, the basic feature f_1 together with the fixed-length detect queries q_d are input to the Transformer decoder to generate the track queries q_{ot}^1 . q_{ot}^1 are used to generated the prediction Y_1 for the T_1 frame and passed through the query interaction module (QIM) to generate the updated track query set q_t^2 for the T_2 frame. For any T_i frame, where $i \in [2, N]$, the updated track query set q_t^i generated by the QIM from the T_{i-1} frame and the detection query set q_d will be concatenated. The concatenated query set together with the basic feature f_i is input to the shared Transformer decoder to generate updated query set q_{ot}^i and the prediction Y_i for the T_i frame. For inference time, such process can be repeated for a whole video sequence. During training phase, the label assignment of each frame between the predictions and GTs is determined by

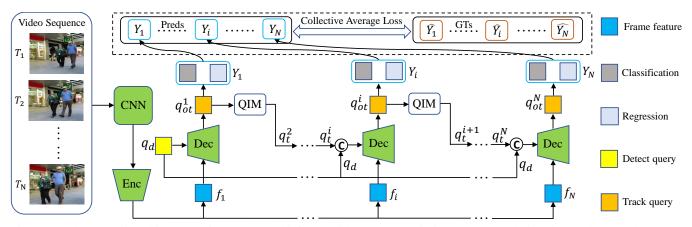


Figure 3: The overall architecture of MOTR. Multi-frame video sequence is input to convolutional neural network (CNN) backbone and Transformer encoder (Enc) to extract multi-frame features $f = \{f_1, f_2, ..., f_N\}$. For T_1 frame, basic feature f_1 and detect query q_d (yellow box) are injected to Transformer decoder (Dec) to produce original track queries q_{ot}^1 , q_{ot}^1 is used to generate the prediction Y_1 for T_1 frame. For any T_i frame, track queries q_t^i transferred from T_{i-1} frame are concatenated with detect query q_d and input to the Dec to produce the q_{ot}^i , q_{ot}^i is employed to produce the prediction Y_i and input to the query interaction module (QIM) to update the representation for T_{i+1} frame. Predictions of the video clip are aggregated together and used to calculate the collective average loss with the ground-truths.

Eq. 1 and Eq. 2. All the predictions of the video clip are collected into a prediction bank $\{Y_1, Y_2, ..., Y_N\}$, which are further supervised by the GTs bank $\{\hat{Y}_1, \hat{Y}_2, ..., \hat{Y}_N\}$ through collective average loss (CAL) described in Sec. 3.6.

3.5 Query Interaction Module

In this section, we describe query interaction module (QIM) in detail. QIM mainly includes object entrance and exit mechanism and temporal aggregation network (TAN).

Object Entrance and Exit As mentioned above, some objects in video sequences may appear or disappear at intermediate frames. Here, we introduce how to deal with the new-born and dead objects in our method. For any T_i frame, track queries q_t^i are concatenated with the detect queries q_d and input to the Transformer decoder, producing the original track queries q_{ot}^i . For clarity, we redrawn it on the left side of Fig. 4. The track queries q_{ot}^i can be divided into two sets: $q_{ot}^i = \{q_{tr}^i, q_{det}^i\}. q_{det}^i$ contains new-born objects while q_{tr}^i includes both tracked and dead objects.

During training (shown in Fig. 4(a)), track queries of dead objects (object "2") in q_{tr}^i are removed based on the comparison between ground-truth \hat{Y}_i and matching result ω_{tr}^i defined in Eq. 2. It means that the corresponding track queries will be filtered if these objects disappear at current frame while the rest of track queries \bar{q}_{tr}^i are reserved. For those new-born objects (object "3"), track queries \bar{q}_{det}^i are kept based on matching result ω_{det}^i defined in Eq. 1.

For the inference (shown in Fig. 4(b)), we use classification scores of prediction Y_i to determine when a track appears and disappears. For new-born objects, track queries in q_{det}^i , whose classification scores are higher than the entrance threshold τ_{en} , are kept while the rest of queries are removed:

$$\overline{q}_{tr}^i = \{ q_k \in q_{tr}^i | s_k > \tau_n \} \tag{3}$$

where s_k is the classification score corresponding to the k^{th} track query q_k in q_{det}^i . For dead objects (object "2"), track

queries in q_{tr}^i , whose classification scores (0.23) lower than the exit threshold τ_{ex} for consecutive M frames, are removed and the rest of track queries (object "1") are kept:

$$\overline{q}_{tr}^{i} = \{q_k \in q_{tr}^{i} | \max\{s_k^{i}, \dots, s_k^{i-M}\} > \tau_{ex}\}$$
 (4)

Temporal Aggregation Network In last section, we described the object entrance and exit mechanism to deal with the entrance and exit objects. Here, we introduce the temporal aggregation network (TAN) to enhance the temporal relation and provide contextual priors for the tracked objects. As shown in Fig. 4(c), the inputs of TAN are the filtered track queries \bar{q}_{tr}^i and \bar{q}_{det}^i for tracked and new-born objects. We also collect the track queries of tracked objects \bar{q}_{tr}^{i-1} for temporal aggregation. The track queries \bar{q}_{tr}^{i-1} first add with \bar{q}_{tr}^i . The resulting queries are input to the multi-head attention (MHA) module as both the query and key elements to generate the attention weights. \bar{q}_{tr}^i is treated as the value element of MHA and updated by dot production:

$$tgt = \sigma_s\left(\frac{(\overline{q}_{tr}^i + \overline{q}_{tr}^{i-1}) \cdot (\overline{q}_{tr}^i + \overline{q}_{tr}^{i-1})^{\mathrm{T}}}{\sqrt{d}}\right) \cdot \overline{q}_{tr}^i$$
 (5)

where T denotes the transpose operation. σ_s is the softmax function and d is the dimension of track queries. After that, the tgt is further refined by a feed forward network (FFN) and the resulting track queries are concatenated with \overline{q}_{det}^i to produce the track query set q_t^{i+1} .

3.6 Collective Average Loss

Training samples are important for temporal modeling of track since MOTR learns temporal variances from data rather than hand-crafted heuristics like Kalman Filtering. Common training strategies, like training within only two frames, fail to generate training samples of long-range object motion, such as re-birth. Different with them, MOTR takes video clips as input. In this way, training samples of long-range object motion can be generated for temporal learning.

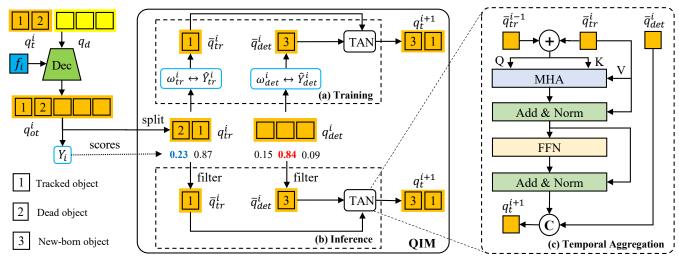


Figure 4: The process of query interaction module (QIM). For T_i frame, the inputs of QIM are the track queries q_{ot}^i generated by Transformer decoder (Dec) and the prediction scores in Y_i . q_{ot}^i is divided into two parts $\{q_{tr}^i, q_{det}^i\}$. q_{tr}^i includes the tracked and exit objects while q_{det}^i includes the new-born objects. During training (shown in (a)), track queries are filtered based on matching results in Eq. 2 and Eq. 1 while they are filtered based on the confidence scores predicted for inference (shown in (b)). Temporal aggregation network (TAN) is introduced to enhance the learning of long-range temporal motion, shown in (c).

Instead of calculating the loss frame-by-frame, our collective average loss (CAL) collects the multiple predictions $Y = \{Y_i\}_{i=1}^N$. Then the loss within the whole video sequence is calculated by GTs $\hat{Y} = \{\hat{Y}_i\}_{i=1}^N$ and the matching results $\omega = \{\omega_i\}_{i=1}^N$. CAL is the overall loss of the whole video sequence, normalized by the number of objects:

$$\mathcal{L}_{o}(Y|_{\omega}, \hat{Y}) = \frac{\sum_{n=1}^{N} (\mathcal{L}(Y_{tr}^{i}|_{\omega_{tr}^{i}}, \hat{Y}_{tr}^{i}) + \mathcal{L}(Y_{det}^{i}|_{\omega_{det}^{i}}, \hat{Y}_{det}^{i}))}{\sum_{n=1}^{N} (V_{i})}$$
(6)

where $V_i = V_{tr}^i + V_{det}^i$ denotes the total number of GTs at T_i frame. V_{tr}^i and V_{det}^i are the numbers of tracked objects and new-born objects at T_i frame, respectively. $\mathcal L$ is the loss of single frame, which is similar to the detection loss in DETR. The single-frame loss $\mathcal L$ can be formulated as:

$$\mathcal{L}(Y_i|_{\omega_i}, \hat{Y}_i) = \lambda_{cls} \mathcal{L}_{cls} + \lambda_{l_1} \mathcal{L}_{l_1} + \lambda_{aiou} \mathcal{L}_{aiou}$$
 (7)

where \mathcal{L}_{cls} is the focal loss (Lin et al. 2017). \mathcal{L}_{l_1} denotes the L1 loss and \mathcal{L}_{giou} is the generalized IoU loss (Rezatofighi et al. 2019). λ_{cls} , λ_{l_1} and λ_{giou} are the corresponding weight coefficients.

3.7 Discussion

Based on DETR, our concurrent works, TransTrack (Sun et al. 2020) and TrackFormer (Meinhardt et al. 2021) also develop the Transformer-based frameworks for MOT. However, our method shows large differences compared to them. TransTrack models a full track as a combination of several independent short tracklets. Similar to the track-by-detection paradigm, TransTrack decouples MOT as two subtasks: 1) detect object pairs as short tracklets within two adjacent frames; 2) associate short tracklets as full tracks by IoU-matching. While for our MOTR, we models a full

track in an end-to-end manner through the iterative update of track query, requiring no IoU/ReID-matching. Track-Former shares the same track modeling with us. However, Track-Former still learns within two adjacent frames. As discussed at Sec. 3.6, learning within short-range will result in relatively weak temporal learning. Therefore, Track-Former employs heuristics, such as Track NMS and Re-ID features, to filter out duplicate tracks. Different with Track-Former, our MOTR learns stronger temporal motion with CAL and TAN, removing the need of those heuristics. For direct comparison with TransTrack and Track-Former, please refer to the Tab. 1.

Method	D-DETR	IoU-Match	Track NMS	Re-ID
TransTrack (Sun et al. 2020)	✓	✓		
TrackFormer (Meinhardt et al. 2021)	✓		✓	✓
Ours	✓ ✓			

Table 1: Comparison with other Transformer-based MOT methods. D-DETR is Deformable DETR (Zhu et al. 2020).

4 Experiments

4.1 Datasets and Metrics

Datasets: MOT16 and MOT17 (Milan et al. 2016) contain the same video sequences, including 7 training sequences and 7 test sequences. The main difference between them is the detection ground-truth labels. In public detection, detection inputs of MOT16 are obtained by the DPM (Felzenszwalb et al. 2009) detector while that of MOT17 are generated by DPM, Faster R-CNN (Ren et al. 2015) and SDP (Yang et al. 2016) object detectors.

Evaluation Metrics: We follow standard evaluation protocols to evaluate our method. The common metrics include Multiple-Object Tracking Accuracy (MOTA), the percentage of Mostly Tracked Trajectories (MT), Mostly Lost Trajectories (ML), Identity Switches (IDS) and Identity F1 Score (IDF1). Among them, IDF1 is used to measure the

Dataset	Tracker	IDF1↑	MOTA↑	MT (%) ↑	ML (%)↓	FP↓	FN↓	IDS↓
	CNN-based:							
	FWT(Henschel et al. 2017)	44.3	47.8	19.1	38.2	8886	85487	852
	MOTDT(Chen et al. 2018)	50.9	47.6	15.2	38.3	9253	85431	792
	GCRA(Ma et al. 2018)	48.6	48.2	12.9	41.1	5104	88586	821
	EAMTT(Sanchez-Matilla et al. 2016)	53.3	52.5	19.0	34.9	4407	81223	910
	Tracktor++(Bergmann et al. 2019)	52.5	54.4	19.0	36.9	3280	79149	682
MOT16	SORTwHPD16(Bewley et al. 2016)	53.8	59.8	25.4	22.7	8698	63245	1423
	smartSORT(Meneses et al. 2020)	56.1	60.4	28.9	21.2	11183	59867	1135
	DeepSORT_2(Wojke et al. 2017)	62.2	61.4	32.8	18.2	12852	56668	781
	JDE(Wang et al. 2020)	55.8	64.4	35.4	20.0	/	/	1544
	Transformer-based:							
	MOTR (Ours)	67.0	66.8	34.1	25.7	10364	49582	586
	CNN-based:							-
	FWT(Henschel et al. 2017)	47.6	51.3	21.4	35.2	24101	247921	2648
	SST(Sun et al. 2019)	49.5	52.4	21.4	30.7	25423	234592	8431
	Tracktor++(Bergmann et al. 2019)	52.3	53.5	19.5	36.6	12201	248047	2072
	Tracktor v2(Bergmann et al. 2019)	55.1	56.5	21.1	35.3	8866	235449	3763
	CTracker(Peng et al. 2020)	57.4	66.6	32.2	24.2	22284	160491	5529
MOT17	CenterTrack(Zhou et al. 2020)	64.7	67.8	/	/	18498	160332	3039
	QuasiDense (Pang et al. 2021)	66.3	68.7	40.6	21.9	26589	146643	3378
	TraDeS (Wu et al. 2021)	63.9	69.1	36.4	21.5	20892	150060	3555
	Transformer-based:							
	TrackFormer (Meinhardt et al. 2021)	63.9	65.0	/	/	70443	123552	3528
	TransTrack(Sun et al. 2020)	63.9	74.5	46.8	11.3	28323	112137	3663
	MOTR (Ours)	67.0	67.4	34.6	24.5	32355	149400	1992

Table 2: Performance comparison between MOTR and existing methods on MOT16 and MOT17 datasets under the private detection protocols. The number is marked in bold if it is the best in each column.

trajectory identity accuracy. MOTA is the primary metric to measure the overall detection and tracking performance.

4.2 Implementation Details

Following the settings in CenterTrack (Zhou et al. 2020), several data augmentation methods, such as random flip and random crop, are adopted. The shorter side of input images is resized to 800 and the maximum size is restricted within 1536. We randomly sample key frames from video sequences with interval to solve the problem of different frame rates. Besides, we erase the tracked queries with the probability p_{drop} to generate more samples for new-born objects and insert track queries of false positives with the probability p_{insert} to simulate the dead objects.

All the experiments are conducted on PyTorch with 8 Tesla V100 GPUs. We built MOTR upon Deformable-DETR (Zhu et al. 2020) with ResNet50 (He et al. 2016) for fast convergence. It is pretrained on COCO detection dataset (Lin et al. 2014). We train our model with the AdamW optimizer for total 200 epochs with the initial learning rate of $2.0 \cdot 10^{-4}$. The learning rate decays to $2.0 \cdot 10^{-5}$ at 150 epochs. The batch size is set to 1 and each batch contains a video clip of 5 frames. For state-of-the-art comparison, we train MOTR on the joint datasets (MOT17 training set and CrowdHuman (Shao et al. 2018) val set). For ∼5k static images in CrowdHuman val set, we apply random shift in (Zhou et al. 2020) to generate video clips with pseudo tracks. The initial length of video clip is 2 and we gradually increase it to 3,4,5 at 50^{th} ,90th,150th epochs, respectively. The progressive increment of video clip improves the training efficiency and stability. For ablation study, we ignore the dataset of CrowdHuman and train MOTR on MOT17 training set.

4.3 State-of-the-art Comparison

As shown in Tab. 2, we compare our approach with previous methods on MOT16 and MOT17 test datasets.

In MOT16, we compare MOTR with JDE (Wang et al. 2020) and DeepSORT_2 (Wojke et al. 2017), which achieve state-of-the-art performance among previous methods in MOTA and IDF1 metrics, respectively. Our method surpasses JDE by 11.2% and DeepSORT_2 by 4.8% on IDF1. Also, MOTR gets fewer IDS than JDE (586 vs. 1544) and DeepSORT_2 (586 vs. 781). As for the MOTA metric, our method also achieves better performance than JDE (66.8 vs. 64.4) and DeepSORT_2 (66.8 vs. 61.4). In MOT17, we compare our MOTR with CNN-based trackers and our concurrent Transformer-based works, TrackFormer (Meinhardt et al. 2021) and TransTrack (Sun et al. 2020). Our method gets higher IDF1 scores, surpassing CenterTrack, TransTrack and TrackFormer by 2.3%, 3.1%, 3.1%, respectively. It is worthy noting that MOTR also produces much fewer IDS (1992 vs. 3039, 1992 vs. 3528 and 1992 vs. 3663 compared to CenterTrack, TrackFormer and TransTrack, respectively). For the MOTA metric, our method achieves better performance than TrackFormer (67.4 vs. 65.0). Interestingly, we find that the performance of TransTrack is much better than our MOTR on MOTA metric. We suppose the decoupling of detection and tracking branches in TransTrack indeed improves the object detection performance. In MOTR, detect and track queries are learned through a shared Transformer decoder. Detect queries are suppressed on detecting tracked objects, limiting the detection performance on new-born objects.

For comprehensive comparison with those state-of-the-

Table 3: Ablation studies validated on the 2DMOT15 set. All experiments use the single feature level with C5 in ResNet50.

(a) The affect of integrating our contributions into the baseline. TAN and CAL denote the temporal aggregation network and collective average loss, respectively.

(b) The impact of video sequence length on the overall
tracking performance in Collective Average Loss during
training.

Track Query	TAN	CAL	MOTA↑	IDF1↑	IDS↓
			-	1.2	33198
\checkmark			37.1	49.8	562
\checkmark	\checkmark		44.9	63.4	257
\checkmark		\checkmark	47.5	56.1	417
\checkmark	\checkmark	\checkmark	53.2	70.5	155

Length	MOTA↑	IDF1↑	FP↓	FN↓	IDS↓
2	44.9	63.4	16866	6649	257
3	51.6	59.4	13347	7102	424
4	50.6	64.0	13888	7104	314
5	53.2	70.5	13549	6466	155

(c) Analysis on random track query erasing probability p_{drop} during training phase.

(d) The effectiveness of random false positive inserting probability p_{insert} during training phase.

p_{drop}	MOTA↑	IDF1↑	FP↓	FN↓	IDS↓
5e-2	49.0	60.4	11787	9810	411
0.1	53.2	70.5	13549	6466	155
0.3	51.1	69.0	14985	5926	180
0.5	48.5	62.0	15579	6356	302

p_{insert}	MOTA↑	IDF1↑	FP↓	FN↓	IDS↓
0.1	51.2	71.7	17972	5935	148
0.3	53.2	70.5	13549	6466	155
0.5	52.1	62.0	13453	6854	345
0.7	50.7	57.7	13073	7768	444

(e) The exploration of different combinations of τ_{ex} and τ_{en} in QIM network.

$ au_{ex}$	0.6	0.6	0.6	0.6	0.5	0.6	0.7	0.8
$ au_{en}$	0.6	0.7	0.8	0.9	0.8	0.8	0.8	0.8
MOTA↑	52.7	52.7	53.2	53.1	53.5	53.2	52.8	52.7
IDF1↑	69.9	69.8	70.5	70.1	70.5	70.5	68.3	66.9
IDS↓	172	181	155	142	153	155	181	225

art approaches, we further conduct the measurements of our MOTR, JDE and CenterTrack on high-order metrics (Luiten et al. 2021). As shown in A.1, MOTR shows better performance on performing tracking association than JDE and CenterTrack under similar localization standard.

4.4 Ablation Study

Our ablation experiments are conducted using the single feature level with DC5 (Zhu et al. 2020) for fast training and validated on the 2DMOT15 dataset.

MOTR Components: Tab. 3a shows the impact of integrating different components. Integrating our components to the baseline can gradually improve overall performance. Using only object query of as original leads to numerous IDS since that most objects are treated as entrance objects. With track query introduced, the baseline is able to handle tracking association and improve IDF1 from 1.2 to 49.8. Further, adding TAN to the baseline improves MOTA by 7.8% and IDF1 by 13.6%. When using CAL during training, there are extra 8.2% and 3.7% improvements in MOTA and IDF1, respectively. It demonstrates that TAN combined with CAL can enhance the learning of temporal motion.

Collective Average Loss: Here, we explored the impact of video sequence length on the tracking performance in CAL. As shown in Tab. 3b, when the length of video clip gradually increases from 2 to 5, MOTA and IDF1 metrics are improved by 8.2% and 3.7%, respectively. Thus, multi-frame CAL can greatly boost the tracking performance. We explained that multiple frames CAL can help network to handle some hard cases such as occlusion scenes. We observed that duplicated boxes, ID switches and object missing in occluded scenes are significantly reduced. To further verify it, we provide some visualizations in the A.2.

Erasing and Inserting Track Query: In MOT datasets,

there are few training samples for two cases: entrance objects and exit objects in video sequences. Therefore, we adopt track query erasing and inserting to simulate these two cases with probability p_{drop} and p_{insert} , respectively. Tab. 3c reports the performance using different value of p_{drop} during training. MOTR achieves the best performance when p_{drop} is set to 0.1. Similar to the entrance objects, track queries transferred from previous frame, whose predictions are false positives, are inserted into current frame to simulate the case of object exit. In Tab. 3d, we explore the impact on tracking performance of different p_{insert} . When progressively increasing the p_{insert} from 0.1 to 0.7, our MOTR achieves the highest score in MOTA metric when the p_{insert} is set to 0.3 while the IDF1 score is continuously decreasing. Object Entrance and Exit Threshold: Tab. 3e investigates the impact of different combination of object entrance threshold τ_{en} and object exit threshold τ_{ex} in QIM. As we vary the object entrance threshold τ_{en} , we can see that the performance is not that sensitive to τ_{en} (within 0.5% on MOTA) and using entrance threshold of 0.8 produces relatively better performance. We also further conduct experiment by varying the object exit threshold τ_{ex} . It is shown that using threshold of 0.5 results in slightly better performance than that of 0.6. In our practice, τ_{en} with 0.6 shows better performance on MOT17 test set.

5 Conclusion

We present MOTR, a truly end-to-end framework for multiple-object tracking. Track queries, served as hidden states, are introduced for iterative tracking prediction. Collective average loss and temporal aggregation network are further proposed to enhance the learning of temporal relation. The framework proposed achieves competitive performance on MOT datasets.

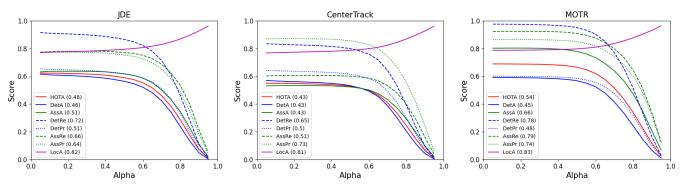


Figure 5: Comprehensive comparison on high-order metrics between JDE, CenterTrack and MOTR. Here, "Alpha" in each figure refers various localization thresholds.

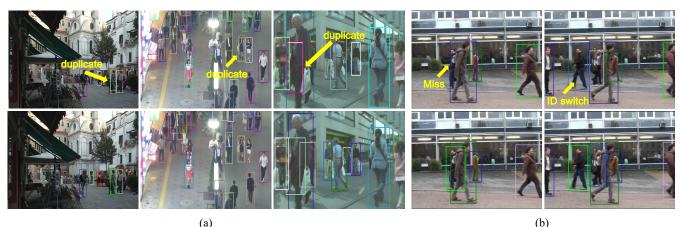


Figure 6: The effect of collective average loss on solving duplicated boxes (a) and ID switch problems (b). The top and bottom rows are the tracking results without and with CAL, respectively.

A APPENDIX

A.1 Comparison on High-order Metrics

As shown in Fig. 5, we compared our MOTR with JDE(Wang et al. 2020) and CenterTrack(Zhou et al. 2020) on high-order metrics (Luiten et al. 2021). Our method shows better performance on tracking association than JDE and CenterTrack under similar localization standard.

A.2 Qualitative Visualizations for CAL

We visualize more qualitative results for CAL in Fig. 6. It indicates that CAL can alleviate the problem of ID switch and object missing in occluded scenes. We explain that CAL can equip our method with strong temporal relation and enhances the tracking and detection simultaneously.

A.3 Ablation Study on Sampling Interval

In Tab. 4, we evaluate the effect of random sampling interval on tracking performance during training. When the sampling interval increases from 2 to 10, the IDS decreases significantly from 209 to 155. During training, the networks are more likely to fall into a local optimal solution because of the small difference in objects' motion if the frames are sampled in a small interval. Appropriate increment on sampling interval can simulate real and complex scenes. When the random sampling interval is greater than 10, the tracking

framework fails to capture such long-range dynamics, leading to relatively worse tracking performance.

Intervals	MOTA↑	IDF1↑	FP↓	FN↓	IDS↓
2	53.3	66.2	13038	6886	209
3	53.2	64.8	12927	7028	218
5	50.8	62.8	12781	8107	324
10	53.2	70.5	13549	6466	155
12	53.1	69	13868	6208	158

Table 4: The effect of random sampling interval on the tracking performance.

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