

# Focus On Details: Online Multi-object Tracking with Diverse Fine-grained Representation

Hao Ren<sup>1</sup>, Shoudong Han<sup>1\*</sup>, Huilin Ding, Ziwen Zhang, Hongwei Wang, Faquan Wang

National Key Laboratory of Science and Technology on Multispectral Information Processing,  
School of Artificial Intelligence and Automation, Huazhong University of Science and Technology  
{haoren2000, shoudonghan}@hust.edu.cn

## Abstract

*Discriminative representation is essential to keep a unique identifier for each target in Multiple object tracking (MOT). Some recent MOT methods extract features of the bounding box region or the center point as identity embeddings. However, when targets are occluded, these coarse-grained global representations become unreliable. To this end, we propose exploring diverse fine-grained representation, which describes appearance comprehensively from global and local perspectives. This fine-grained representation requires high feature resolution and precise semantic information. To effectively alleviate the semantic misalignment caused by indiscriminate contextual information aggregation, Flow Alignment FPN (FAFPN) is proposed for multi-scale feature alignment aggregation. It generates semantic flow among feature maps from different resolutions to transform their pixel positions. Furthermore, we present a Multi-head Part Mask Generator (MPMG) to extract fine-grained representation based on the aligned feature maps. Multiple parallel branches of MPMG allow it to focus on different parts of targets to generate local masks without label supervision. The diverse details in target masks facilitate fine-grained representation. Eventually, benefiting from a Shuffle-Group Sampling (SGS) training strategy with positive and negative samples balanced, we achieve state-of-the-art performance on MOT17 and MOT20 test sets. Even on DanceTrack, where the appearance of targets is extremely similar, our method significantly outperforms ByteTrack by 5.0% on HOTA and 5.6% on IDF1. Extensive experiments have proved that diverse fine-grained representation makes Re-ID great again in MOT.*

## 1. Introduction

As a fundamental task in computer vision, multi-object tracking (MOT) is crucial for automatic driving, video

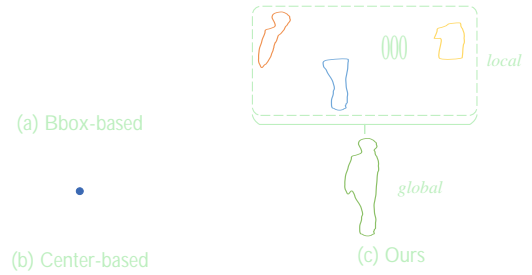


Figure 1. **Comparison with different methods of appearance representation:** (a) Bbox-based, (b) Center-based, (c) global-local fine-grained representation (ours).

surveillance, etc. MOT aims to localize targets and maintain their unique identities. Recent MOT methods [3, 4, 48, 50, 54] mainly follow the paradigm of tracking-by-detection, and divide tracking into two independent steps: detection and association. The detector detects targets in each frame first, and then appearance representation and position information are employed as the association basis to link targets with the corresponding trajectories. As the inherent attributes of the target, appearance and position complement each other in the association.

However, due to targets or camera motion, intra-class and inter-class occlusion are inevitable, which puts forward stricter requirements for appearance representation. As shown in Fig. 1a and Fig. 1b, these methods extract the features of the bounding box region or the center point as appearance embeddings. However, these coarse-grained global embeddings are extremely sensitive to noise, so that become unreliable once the signal-to-noise ratio is reduced. With the headway of the detector [5, 11, 27, 35, 58], appearance representation gradually cannot keep the same performance as detection. Some researchers [54] find that simply using position cues is enough to obtain satisfactory results, while appearance cues are unfavorable for further improvement.

To break this situation, we re-examine the recent appearance-based methods. The bbox-based methods [38]

<sup>1</sup> Equal contribution  
Corresponding author

in Fig. 1a adopt global average pooling, which converts features of the bounding box region into appearance embeddings. These methods equally treat target and interference features (background and other objects), which is unreasonable. As shown in Fig. 1b, researchers [49, 55, 57] notice this issue and utilize features at the target centers as their appearance embeddings, eliminating interference from the background as much as possible. Despite this, when the target is occluded, the feature at its center is still inevitably interfered with noise information from other objects. The fuzziness of global representation has become an impediment of these methods. On the contrary, our method focuses on different local details of targets, which is illustrated in Fig. 1c. Fine-grained global and local representations complement each other and jointly describe appearance. When the target is occluded, our method can still identify it according to visible parts, similar to human judgment.

As the basis of fine-grained representation, target feature maps require high-resolution and unambiguous semantic information. Shallow or deep outputs cannot meet these two requirements simultaneously. Therefore, it is feasible to enrich the semantic information of shallow features or improve the resolution of deep features. To reduce the burden, researchers usually adopt FPN [21] to aggregate multi-scale shallow feature maps indiscriminately, which causes semantic misalignment among features with different resolutions. Specifically, there is a spatial misalignment between the late feature maps after up-sampling and the early feature maps.

To solve this issue, we construct a *Flow Alignment FPN* (FAFPN) to learn the semantic flow among feature maps with different scales and effectively broadcast high-level features to high-resolution features. FAFPN aligns feature maps by semantic flow and aggregates context information to enrich semantic information while maintaining high resolution. Further, *Multi-head Part Mask Generator* (MPMG) is proposed to generate part masks for detailed representations without label supervision. Inspired by multi-head self-attention in Transformer [37], MPMG implements a multi-branch parallel structure, which can efficiently and comprehensively focus on different parts of the target. Combining FAFPN and MPMG, we can obtain a diverse fine-grained representation, including diverse local embeddings and background-filtered global embeddings.

In the training phase, some current MOT methods [20, 55] train Re-ID (re-identification) by following the video sequence or shuffling all video frames. The former does not disperse training data, while the latter is positive and negative samples imbalanced. To train Re-ID more reasonably, we propose a training strategy named *Shuffle-Group Sampling* (SGS). In this strategy, we group video frames into short segments in their order and then shuffle these segments. SGS disperses data and balances pos-

itive and negative samples. Our model incorporates all the above proposed techniques, named *fine-grained representation tracker* (FineTrack).

The main contributions of our work can be summarized as follows:

- We propose a *Flow Alignment FPN* (FAFPN). It learns the semantic flow among feature maps with different resolutions to correct spatial dislocation. Feature maps after FAFPN include high resolution and precise semantic information, which is the basis of fine-grained representation.
- We construct a *Multi-head Part Mask Generator* (MPMG) to focus on details of targets. MPMG employs self-attention to filtrate background noise and extract global-local embeddings to represent targets comprehensively.
- *Shuffle-Group Sampling* (SGS) is proposed to disperse training data and balance positive and negative samples. It reduces oscillation in model convergence to achieve better performance.

## 2. Related Work

**Tracking-by-detection.** With the development of detection, many works [1, 24, 26, 42] adopt the tracking-by-detection paradigm, and divide MOT into detection and association. The trackers following this paradigm first detect objects in video frames and then associate them dependent on their identity information. Some works [1, 10, 31, 34] model object movement for identity association. SORT [3] relies on the Kalman Filter [15] to predict future positions of the targets, calculates their overlap with detection, and utilizes the Hungarian algorithm [17] for identity association. When the target moves irregularly or is occluded, only using motion information is not enough to achieve better performance. Based on SORT [3], DeepSORT [43] introduces the appearance information of targets to enhance identity embedding.

Appearance and motion, as inherent properties of targets, are not independent but complementary while tracking. However, appearance does not always provide reliable clues for identification, particularly when targets are occluded. Our method focuses on diverse details of targets and constructs global-local fine-grained representation, which achieves better performance in occlusion scenes.

**Re-ID in MOT.** Some works [9, 50, 59] crop the image regions of detections and extract features with an extra Re-ID model. These works treat detection and Re-ID as independent tasks, imposing additional parameter burdens. To solve this problem, JDE [42] and FairMOT [55] implement a branch the same as detection for appearance representation. The structure of the multi-task branches achieves impressive performance but also raises an additional issue: com-

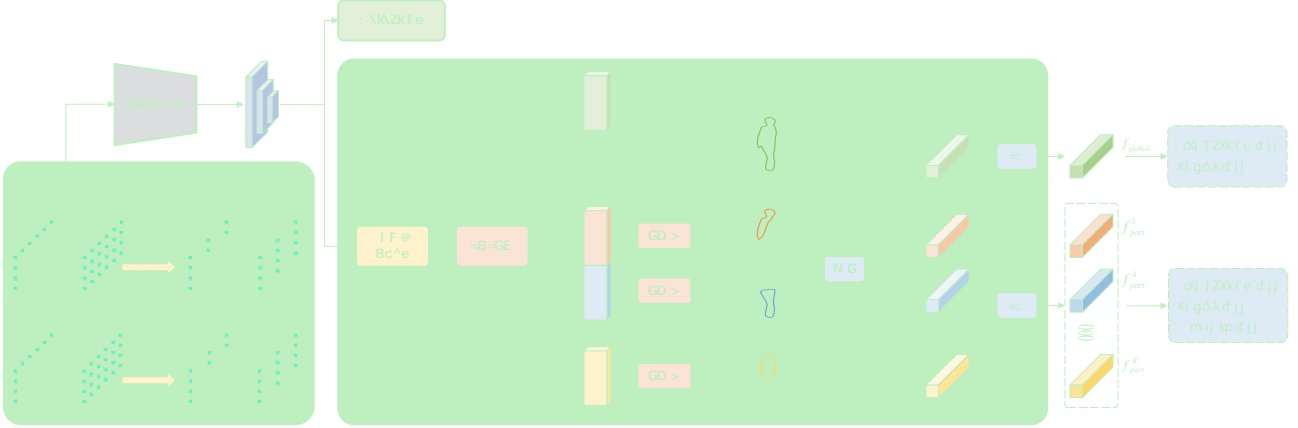


Figure 2. **Overall pipeline of FineTrack.** FineTrack comprises 5 steps: (1) SGS divides videos into groups and shuffles them. (2) Extract feature maps of the input frame for detection. Meanwhile, multi-scale shallow feature maps are obtained for ROIAlign to output target feature maps with different resolutions. (3) FAFPN aligns target feature maps and aggregates their context information for  $F_{mask}$  and  $F_{reid}$ . (4) Divide  $F_{mask}$  into  $K$  blocks along their channel and employ multi-head PMG to generate part masks  $M_{part}$ . Concatenate  $M_{part}$  and adopt  $Max$  of channel to form global masks  $M_{global}$ . (5)  $F_{global}$  and  $F_{part}$  can be obtained by a weighted pooling. Then two fully connected layers convert them into global and part embedding:  $f_{global}$  and  $f_{part}$ , respectively.

petition caused by different goals for detection and Re-ID. To alleviate this conflict, CStrack [20] constructs a CCN module to extract general and specific features more suitable for detection and Re-ID. However, these appearance-based methods extract the features of the boundary box region or the center point as appearance representation, which are inevitably interfered with irrelevant information. They focus on generating more discriminative global embedding instead of exploring more detailed appearance cues.

Although well-designed Re-ID modules can improve performance, global features are still prone to ambiguity. With a high-performance detector, the associator can link most targets only with motion cues. The global representation is also impotent for the remaining targets incorrectly tracked due to occlusion or other factors. Using global appearance cues at this point can even compromise tracking accuracy. Instead, our method focus on the details of targets. Following this idea, we construct the FAFPN to align and aggregate high-resolution shallow feature maps and feed them into the MPMG to obtain fine part masks. Further, part masks of targets are employed to extract the fine-grained global-local appearance embedding, which can more comprehensively represent the identity.

### 3. Methodology

#### 3.1. Overview

In this work, we adopt the high-performance detector YOLOX [11] to detect targets. As shown in Fig. 2, during training, SGS groups video frames by sampling them sequentially, ensuring targets with positive and negative samples. After shuffling, these grouped data are fed into the

Backbone to obtain feature maps with different resolutions. Then, we adopt ROIAlign to crop and scale feature maps of the bbox regions to get the multi-scale feature maps of targets. Immediately, FAFPN aligns these target feature maps from different resolutions and aggregates them into fine-grained feature maps:  $F_{mask}$  and  $F_{reid}$  for mask generation and appearance embedding, respectively. After slicing  $F_{mask}$  along the channel dimension, the features are fed into separate *Part-Mask Generator* (PMG) to generate target masks. Further,  $F_{global}$  and  $F_{part}$  can be obtained by a weighted pooling. These embeddings are fed into two fully connected layers that do not share parameters to output  $f_{global}$  and  $f_{part}$ . For  $f_{global}$ , we calculate Classification loss and Triplet loss. For  $f_{part}$ , a diversity loss is added to expand the discrepancy among different part features.

#### 3.2. Flow Aligned FPN

As a classical method for feature aggregation, FPN [21] has been extensively applied in different computer vision tasks. However, step-by-step downsampling and indiscriminate context aggregation cause semantic misalignment among feature maps of different scales. Fuzzy semantic information have a significant impact on visual tasks which require detailed descriptions. To obtain fine-grained features, we employ the *Flow Alignment Module* (FAM) [14, 19] to generate semantic flow among feature maps of different resolutions. The semantic flow can guide alignment and eliminate spatial dislocation among feature maps from different scales. Furthermore, we utilize the FAM to optimize the aggregation process of FPN and then construct a *Flow Alignment FPN* (FAFPN).

The overall structure of FAFPN is shown in Fig. 3. Res-



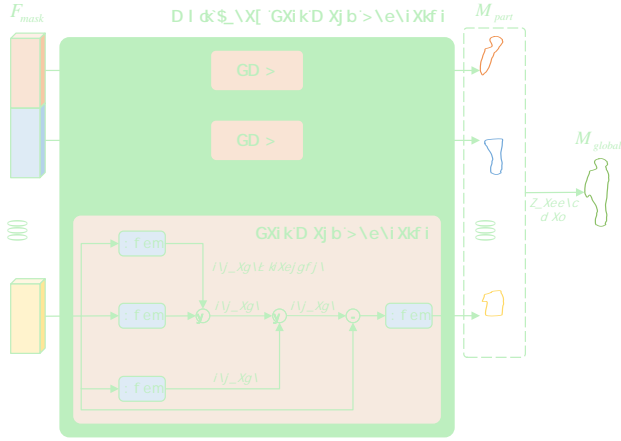


Figure 5. **Illustration of MPMG.** Multiple parallel PMG branches focus on different parts of the target and generate part masks.

identity of targets.

To solve the above problem, we construct the *Shuffle-Group Sampling* (SGS) training strategy. Different from random sampling, SGS adopts sequential sampling to group video frames. In this way, targets in the same batch hold positive samples with the same identity, thus alleviating the problem of imbalanced positive and negative samples caused by random sampling. In training, we disrupt the order of grouped data to reduce convergence fluctuations. This strategy allows contiguous batches to originate from different videos and form a sequence of track segments with significant appearance variations. Such a discrete distribution of training data optimizes the convergence direction of the model.

**Training Loss.** SGS enables a batch of targets to contain both positive and negative samples, so the model can be optimized using Triplet loss, which is extensively applied in Re-ID methods. The part and global features are denoted as  $f_{part} = \{f_p^{n,k}, n \in [1, 2, \dots, N], k \in [1, 2, \dots, K]\}$  and  $f_{global} = \{f_g^n, n \in [1, 2, \dots, N]\}$ . Here  $N$  represents the number of targets in the image and each target is composed of  $K$  parts. Thus,  $f_p^{n,k}$  means the  $k_{th}$  part feature of the  $n_{th}$  target, and  $f_g^n$  represents the global feature of the  $n_{th}$  target.

Then we can calculate the Triplet loss with a soft margin for part features based on Eq. (1):

$$L_{tri}^p(k) = \frac{1}{K} \sum_{k=1}^K Triplet(f_p^k), \quad (1)$$

where  $Triplet(\cdot)$  is the same as [13] and  $f_p^k$  represents the  $k_{th}$  part features of  $n$  targets in the image.

Similarly, the Triplet loss of the global features is based on Eq. (2):

$$L_{tri}^g(k) = Triplet(f_{global}), \quad (2)$$

After obtaining  $K$  part features,  $K$  combinations of Linear layer and Softmax are respectively applied to get the classification result vectors  $P = \{p_n^k, k \in [1, 2, \dots, K], n \in [1, 2, \dots, N]\}$ . The meanings of  $K$  and  $N$  are the same as in  $f_{part}$ .  $p_n^k$  represents the classification vector of the  $k_{th}$  part feature of the  $n_{th}$  target. The dimension of  $p_n^k$  is  $M$ , which is also the number of all targets in the datasets. For target identity labels, we denote them as  $Y = \{y_{n,m}, n \in [1, 2, \dots, N], m \in [1, 2, \dots, M]\}$ ,  $y_{n,m}$  means whether the  $n_{th}$  target has the same identity as the  $m_{th}$  target in ID labels, with a value of 0 or 1. According to the above definition, we can calculate the classification loss of the  $k_{th}$  part feature of the  $n_{th}$  target with Eq. (3):

$$L_{n,k}^p(m) = y_{n,m} \log(p_n^k(m)), m \in [1, 2, \dots, M] \quad (3)$$

Further, we calculate the classification loss of part features based on with Eq. (4):

$$L_{cls}^p = -\frac{1}{K \cdot N} \sum_{k=1}^K \sum_{n=1}^N \sum_{m=1}^M L_{n,k}^p(m) \quad (4)$$

Similarly, the classification loss of global features is:

$$L_{cls}^g = -\frac{1}{N} \sum_{n=1}^N \sum_{m=1}^M y_{n,m} \log(g_n(m)), \quad (5)$$

where  $g_n$  is the classification vector of the  $n_{th}$  target's global feature.

Due to the peculiarities of multi-branch structures, using only classification loss and Triplet loss does not ensure that the model focuses on different parts of the target. To avoid multiple branches gazing at similar details, we employ the diversity loss  $L_{div}$  in Eq. (6) to distance different part features of the same target:

$$L_{div} = \frac{1}{N \cdot K(K-1)} \sum_{n=1}^N \sum_{k_i \neq k_j}^K \frac{f_p^{n,k_i} \cdot f_p^{n,k_j}}{\|f_p^{n,k_i}\|_2 \cdot \|f_p^{n,k_j}\|_2} \quad (6)$$

The purpose of diversity loss is intuitive, which is to keep the cosine similarity between different part features of the same target as low as possible.

We combine the above losses into a final training loss:

$$L = \alpha \cdot (L_{cls}^p + L_{tri}^p) + \beta \cdot (L_{cls}^g + L_{tri}^g) + \gamma \cdot L_{div}, \quad (7)$$

where  $\alpha$ ,  $\beta$ , and  $\gamma$  are used to adjust the proportion of different losses and we set  $\alpha = 0.5$ ,  $\beta = 0.3$ ,  $\gamma = 2$ .

**Inference.** Based on ByteTrack [54], we add a method similar to DeepSort [43] that calculates Re-ID features into feature distance matrix. It is worth mentioning that we concatenate part features of targets with global features as Re-ID features.

We adopt the exponential moving average (EMA) mechanism to update the features  $\tilde{f}_i^t$  of matched tracklets for the  $i_{th}$  tracklet at frame  $t$  based on Eq. (8), as in [55].

$$\tilde{f}_i^t = \tilde{f}_i^{t-1} + (1 - \alpha) f_i^t, \quad (8)$$

where  $f_i^t$  is the feature of the current matched detection, and  $\alpha = 0.9$  is a momentum term.

In the tracking algorithm, the feature distance matrix  $d_{feat}$  is:

$$d_{feat} = 1 - \text{Similarity}(\tilde{f}^{t-1}, f^t), \quad (9)$$

where  $\text{Similarity}(\cdot)$  outputs the cosine similarity matrix between tracklets features  $\tilde{f}^{t-1}$  and targets features  $f^t$ .

Meanwhile, we can calculate the IoU distance matrix  $d_{IoU}$  base on Eq. (10).

$$d_{IoU} = 1 - \text{IoU}(b_{det}, b_{pre}), \quad (10)$$

where  $\text{IoU}(\cdot)$  outputs the IoU matrix between detection bboxes  $b_{det}$  and prediction bboxes  $b_{pre}$ .

To exclude the interference of distant targets, we only consider feature distances between pairs of targets with the IoU distance less than 1, which means there is bounding box overlap. The optimized feature distance matrix  $\tilde{d}_{feat}$  is:

$$\tilde{d}_{feat} = 1 - (1 - d_{feat}) \cdot (d_{IoU} < 1) \quad (11)$$

After squaring the product of the optimized feature distance matrix and IoU matrix, the final distance matrix is obtained for the association with Eq. (12):

$$d = \sqrt{\tilde{d}_{feat} \cdot d_{IoU}} \quad (12)$$

Finally, we set the association threshold to 0.5.

## 4. Experiments

### 4.1. Settings

**Datasets.** To verify the effectiveness of FineTrack, we test it on MOT17 [23], MOT20 [7], and DanceTrack [32] datasets. MOT17 and MOT20 datasets provide training sets but do not contain validation sets. The test metric only can be obtained by uploading the tracking results to the MOTChallenge website for evaluation. Therefore, in the ablation experiment phase, we divided the first half of each video of the MOT17 dataset into the training set and the second half as the validation set. Due to the difference between detection and Re-ID, we train them separately. For testing on MOT17, we train a detector using the same datasets as ByteTrack, including CrowdHuman [30], MOT17, Cityperson [52], and ETHZ [8], and then freeze the trained detector parameters and train Re-ID separately on MOT17.

DanceTrack is a large-scale multi-object tracking dataset for occlusions, frequent crossing, uniform appearance, and

Method	HOTA	IDF1	MOTA	FP	FN	IDs
<i>MOT17 private detection</i>						
DAN [34]	39.3	49.5	52.4	25423	234592	8431
TubeTK [24]	48.0	58.6	63.0	27060	177483	4137
MOTR [51]	-	66.4	65.1	45486	149307	2049
CTracker [26]	49.0	57.4	66.6	22284	160491	5529
MAT [12]	53.8	63.1	69.5	30660	138741	2844
QuasiDense [25]	53.9	66.3	68.7	26589	146643	3378
TransTrack [33]	54.1	63.5	75.2	50157	86442	3603
TransCenter [46]	54.5	62.2	73.2	23112	123738	4614
GSDT [41]	55.2	66.5	73.2	26397	120666	3891
PermaTrackPr [36]	55.5	68.9	73.8	28998	115104	3699
SOTMOT [56]	-	71.9	71.0	39537	118983	5184
FUFET [29]	57.9	68.0	76.2	32796	98475	3237
MTrack [48]	-	72.1	73.5	53361	101844	2028
FairMOT [55]	59.3	72.3	73.7	27507	117477	3303
CSTrack [20]	59.3	72.6	74.9	23847	114303	3567
SiamMOT [31]	-	72.3	76.3	-	-	-
ReMOT [47]	59.7	72.0	77.0	33204	93612	2853
Semi-TCL [18]	59.8	73.2	73.3	22944	124980	2790
CorrTracker [39]	60.7	73.6	76.5	29808	99510	3369
RelationTrack [49]	61.0	74.7	73.8	27999	118623	1374
TransMOT [6]	61.7	75.1	76.7	36231	93150	2346
ByteTrack [54]	63.1	77.3	<b>80.3</b>	25491	<b>83721</b>	2196
<b>FineTrack</b>	<b>64.3</b>	<b>79.5</b>	80.0	<b>21750</b>	90096	<b>1272</b>
<i>MOT20 private detection</i>						
MLT [53]	43.2	54.6	48.9	45660	216803	2187
TransTrack [33]	48.5	59.4	65.0	27197	150197	3608
FairMOT [55]	54.6	67.3	61.8	103440	88901	5243
Semi-TCL [18]	55.3	70.1	65.2	61209	114709	4139
CSTrack [20]	54.0	68.6	66.6	25404	144358	3196
GSDT [41]	53.6	67.5	67.1	31913	135409	3131
SiamMOT [31]	-	69.1	67.1	-	-	-
RelationTrack [49]	56.5	70.5	67.2	61134	104597	4243
SOTMOT [56]	-	71.4	68.6	57064	101154	4209
ByteTrack [54]	61.3	75.2	77.8	26249	<b>87594</b>	1223
<b>FineTrack</b>	<b>63.6</b>	<b>79.0</b>	<b>77.9</b>	<b>24439</b>	89012	<b>980</b>

Table 1. Comparison of the state-of-the-art methods under the private detection on the **MOT17** and **MOT20** test set. The best results are marked in **bold** and our method is highlighted in **pink**.

human body tracking with different body postures, with 100 videos. It uses 40, 25, and 35 videos as training, verification, and test set, respectively. The pedestrians in DanceTrack wear remarkably similar clothes, which is a massive challenge for Re-ID. Many existing methods that rely on Re-ID are at a disadvantage on this dataset.

**Metrics.** We use CLEAR-MOT Metrics [2], such as HOTA, MOTA, IDF1, IDs, FP, FN, etc., to evaluate the tracking performance. MOTA focuses on detection performance, and IDF1 [28] emphasizes association performance. Compared with them, HOTA [22] comprehensively balances detection, association, and localization effects. To accurately measure the performance of Re-ID and exclude the influence



Method	HOTA	IDF1	MOTA	AssA	DetA
CenterTrack [57]	41.8	35.7	86.8	22.6	<b>78.1</b>
FairMOT [55]	39.7	40.8	82.2	23.8	66.7
QuasiDense [25]	45.7	44.8	83.0	29.2	72.1
TransTrack [33]	45.5	45.2	88.4	27.5	75.9
TraDes [45]	43.3	41.2	86.2	25.4	74.5
ByteTrack [54]	47.7	53.9	89.6	32.1	71.0
<b>FineTrack</b>	<b>52.7</b>	<b>59.8</b>	<b>89.9</b>	<b>38.5</b>	<b>72.4</b>

Table 2. Comparison of the state-of-the-art methods on the **DanceTrack** test set. The best results are marked in **bold** and our method is highlighted in **pink**.

of detection and association, Rank-1 and mAP are utilized as metrics to measure the ability of Re-ID feature representation.

**Implementation details.** The partial feature and global feature dimensions are 128 and 256. The number of target masks  $K$  is set as 6 in MOT17 and 4 in MOT20. The detector training Settings are consistent with Bytetrack. During training, the batch size is set to 8. The model parameters are updated using the Adam optimizer [16] with an initial learning rate of  $2 \times 10^{-4}$  and 20 training epochs. The learning rate is reduced to  $2 \times 10^{-5}$  at the 10<sup>th</sup> epoch.

## 4.2. Comparison with the State-of-the-art Methods

In this part, we compare the performance of FineTrack with previous SOTA methods on three benchmarks, i.e., MOT17, MOT20 and DanceTrack. Notably, some MOT methods utilize extra Re-ID models and Re-ID datasets to improve their performance of identity embedding. For a fair comparison, FineTrack only uses MOT datasets for Re-ID training and does not use any additional labels for supervision, such as masks, etc.

**MOT17:** FineTrack shows significant advantages without introducing extra Re-ID models and datasets containing a large amount of identity information. As shown in Tab. 1, FineTrack method achieves the best tracking accuracy on the MOT17 datasets (i.e. 64.3% HOTA, 79.5% IDF1 and 80.0% MOTA, etc.). In cases where using detection simply can obtain excellent tracking accuracy, FineTrack achieves further improvement compared to ByteTrack (1.2% HOTA and 2.2% IDF1), which also adopts YOLOX as the detector. This demonstrates that our proposed fine-grained appearance representation dramatically improves the performance of identity embedding. Compared with other MOT methods, the advantages of FineTrack are more prominent.

**MOT20:** Compared with MOT17, MOT20 is more crowded, which causes frequent and dense occlusion. As shown in Tab. 1, FineTrack outperforms ByteTrack by 2.3% on HOTA, 3.8% on IDF1 with superior identity embeddings while reducing IDs from 1223 to 980. FineTrack has a stable and excellent performance in dense pedestrian scenes,

Method	Metrics	
	Rank-1	mAP
1 FineTrack(train by the order of videos )	89.7	56.7
2 FineTrack(shuffle all video frames)	90.9	60.4
3 FineTrack(w SGS)	<b>92.3</b>	<b>61.8</b>

Table 3. **Ablation study of SGS.** The first row does not disturb the video frames and trains in their order. The second row represents shuffling all the video frames. The last row is our SGS training strategy. (SGS: Shuffle-Group Sampling)

highlighting the role of fine-grained appearance embedding. **DanceTrack:** Pedestrians in DanceTrack dress very similarly and have complex body pose variations, making appearance-based methods perform poorly. FineTrack has excellent appearance modeling capabilities, as shown in Tab. 2, where we outperform ByteTrack entirely (5.0% on HOTA and 5.6% on IDF1, etc.). This further indicates the superiority of fine-grained appearance representations.

## 4.3. Ablation Studies

In this section, we verify the effectiveness of FineTrack through ablation studies. All experiments are conducted on the MOT17 dataset. Since the MOT Challenge does not provide validation sets, we split the MOT17 dataset into two parts. The first half of each video serves as the training set and the second half as the validation set. To fairly measure the performance of identity embedding, experiments in Tab. 3, Tab. 4 and Tab. 5 utilize the Ground Truth of bboxes as input, which can eliminate the interference caused by false detection. Tab. 3 verifies the effectiveness of the SGS training strategy, which is employed in the remaining ablation studies.

**Analysis of SGS.** To validate the advantages of our proposed SGS training strategy, we compare it with two other typical training methods, as reported in Tab. 3. Our proposed SGS is superior to the first training method by 2.6% on Rank-1 and 5.1% on mAP. While shuffling all video frames gets improvement (1.2% on Rank-1 and 3.7% on mAP) over training in the order of video frames, there is still a gap of 1.4% on both Rank-1 and mAP compared with SGS. This ablation experiment proves the effectiveness of FineTrack and reflects the importance of positive and negative samples balanced and discrete distribution of training data for training Re-ID.

**Component-wise Analysis.** In this part, we verified the effectiveness of FAFPN and MPMG through ablation experiments. As shown in Tab. 4, FineTrack effectively improves the performance of appearance embeddings. Because YOLOX [11] cannot extract Re-ID features, we use FPN [21] to aggregate multi-scale feature maps and then adopt Global Average Pooling (GAP) to obtain appearance embeddings. Finally, we combine FPN and GAP as our

Method	Components				Metrics	
	FPN	FAFPN	GAP	MPMG	Rank-1	mAP
1 Baseline					88.3	50.4
2					89.8	55.7
3					91.8	58.2
4 <b>FineTrack</b>					<b>92.3</b>	<b>61.8</b>

Table 4. **Ablation study of the components in FineTrack.** The first row is our baseline, and the last row is the metrics that can be obtained by adopting our proposed FAFPN and MPMG. (GAP: Global Average Pooling, FAFPN: Flow Alignment FPN, MPMG: Multi-head Part Mask Generator)

Method	Components		Metrics	
	GAP	MPMG	Rank-1	mAP
1 FineTrack(w/o FAM)			91.7	57.9
2 FineTrack(w/o FAM)			92.0	61.1
3 FineTrack(w FAM)			91.8	58.2
4 FineTrack(w FAM)			<b>92.3</b>	<b>61.8</b>

Table 5. **Ablation study of FAM.** Re-ID embedding can be extracted through GAP or MPMG. We verify the effectiveness of FAM in these two cases. (FAM: Flow Alignment Module)

baseline (row 1). Compared with baseline indicators, our method (row 4) outperforms the baseline by 4% on Rank-1 and 11.4% on mAP, demonstrating the value of exploring fine-grained appearance representation.

Then, we analyze the effectiveness of each module separately. For multi-scale feature maps aggregation, replacing FPN with FAFPN (row 3) can achieve improvement (3.5% on Rank-1 and 7.8% on mAP) when generating Re-ID embeddings with GAP. Furthermore, when MPMG replaces GAP, using FAFPN (row 4) is better than using FPN (row 2) by 2.5% on Rank-1 and 6.1% on mAP. This indicates that FAFPN captures feature context information more effectively than FPN. At the same time, employing MPMG to extract Re-ID embeddings (row 2) is better than the baseline (1.5% on Rank-1 and 5.3% on mAP). When FAFPN replaces FPN, MPMG is 0.5% and 3.6% higher than GAP on Rank-1 and mAP. MPMG focuses on the discriminative details of the target and can describe the appearance of targets more comprehensively than GAP.

**Analyze of FAM.** In this part, we conducted ablation experiments with or without FAM under the effect of GAP or MPMG, as reported in Tab. 5. Specifically, when GAP is used to generate Re-ID embeddings, employing FAM (row 1 and row 3) can increase 0.1% on Rank-1 and 0.3% on mAP. At the same time, if we adopt MPMG to extract Re-ID embeddings (row 2 and row 4), FAM can get the improvement (0.3% on Rank-1 and 0.7% on mAP), which is significantly better than adding FAM when using GAP. GAP is a global representation that aggregates all information indis-

Method	MOTA	IDF1	IDs
1 Baseline	75.5	77.8	253
2 Baseline+FAFPN	76.0	78.9	459
3 Baseline+MPMG	76.4	79.7	451
4 Baseline+FAFPN+MPMG	<b>77.0</b>	<b>81.1</b>	<b>115</b>

Table 6. **Ablation study of our components when tracking.** The same association strategy is adopted for our proposed module to obtain the tracking results.

criminally. On the contrary, MPMG generates part masks to distinguish features explicitly and can guide FAM to perform pixel-level alignment more reasonably, even without mask label supervision.

**Analyze of our components when tracking.** We adopt the same association strategy to prove the effectiveness of different components in FineTrack when tracking. As shown in Tab. 6, using FAFPN or MPMG alone also improves the tracking performance. When combining these two modules, there is a significant advantage over the baseline (1.5% on MOTA, 3.3% on IDF1, and the IDs decreases from 253 to 115), demonstrating the effectiveness of FineTrack.

## 5. Conclusion

In this work, we have argued that diverse fine-grained representation is essential for MOT. However, existing methods focus on coarse-grained global features, which are extremely sensitive to noise. To effectively filter irrelevant information, we propose to explore diverse fine-grained appearance representation to obtain more comprehensive embeddings. As reported in the ablation studies, our presented FAFPN has great advantages in terms of aligning semantic and aggregating contextual information. Meanwhile, our constructed MPMG can effectively focus on different parts of the target without label supervision. In the training phase, we propose the SGS training strategy to improve the model performance effectively. We have verified the effectiveness of our proposed FineTrack on three public benchmarks (MOT17, MOT20, and DanceTrack) and achieved state-of-the-art performance. The experiment results indicate that diverse fine-grained representation can significantly improve the performance of Re-ID in MOT. We hope this work can be a new solution for appearance representation to generate discriminative identity embeddings.

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