ENSEMBLEMOT: A STEP TOWARDS ENSEMBLE LEARNING OF MULTIPLE OBJECT TRACKING

Yunhao Du¹, Zihang Liu¹, Fei Su¹,²

¹ Beijing University of Posts and Telecommunications
² Beijing Key Laboratory of Network System and Network Culture, China
{dyh_bupt, henry0820, sufei}@bupt.edu.cn

ABSTRACT

Multiple Object Tracking (MOT) has rapidly progressed in recent years. Existing works tend to design a single tracking algorithm to perform both detection and association. Though ensemble learning has been exploited in many tasks, i.e., classification and object detection, it hasn’t been studied in the MOT task, which is mainly caused by its complexity and evaluation metrics. In this paper, we propose a simple but effective ensemble method for MOT, called EnsembleMOT, which merges multiple tracking results from various trackers with spatio-temporal constraints. Meanwhile, several post-processing procedures are applied to filter out abnormal results. Our method is model-independent and doesn’t need the learning procedure. What’s more, it can easily work in conjunction with other algorithms, e.g., tracklets interpolation. Experiments on the MOT17 dataset demonstrate the effectiveness of the proposed method. Codes are available at https://github.com/dyhBUPT/EnsembleMOT.

Index Terms— Multiple Object Tracking, Ensemble Learning

1. INTRODUCTION

Multiple Object Tracking (MOT) aims to detect and track all specific classes of objects frame by frame, which plays an essential role in video analysis and understanding. In the past few years, the MOT task is dominated by the tracking-by-detection (TBD) paradigm [3, 4], which performs detection per frame and formulates the MOT problem as a data association task. Recently, some works integrate the detector and embedding model (i.e., appearance or motion embedding) into a unified framework, which can benefit from multi-task learning and tend to achieve a better speed-accuracy trade-off [1, 5].

Ensemble learning [6] generally refers to training and/or combining multiple models, which is widely used in machine learning [7, 8, 9, 10] and computer vision [11, 12, 13, 14]. For example, for image classification, Wortsman et al. proposes Model Soups to average weights of multiple models to improve the classification accuracy [11]. To estimate more stable and accurate pseudo labels for semi-supervised image classification, Temporal Ensembling [12] aggregates the predictions of multiple previous network evaluations into an ensemble prediction. For the object detection task, Soft-NMS [13] and WBF [14] are widely used to combine results from multiple detectors.

Ensemble methods are also used in several MOT works. Peng et al. proposes the Layer-wise Aggregation Discriminative Model (LADM) [15], which uses the weighted average of predictions from three softmax layers to judge whether a detection box represents a person or not. However, it works in the detection procedure, and is essentially not for the tracking algorithm. Inspired by SoftNMS, TrackNMS is designed in GIAOTracker [16] to fuse multiple tracking results. It first sorts trajectories by the average confidence scores, and then performs non-maximum suppression (NMS) based on the temporal IoU. Though it is designed for combining multiple trackers, it is evaluated by the score-based metrics mAP [17], in which redundant low-score results can benefit performance. Instead, the instance-based metrics, i.e., MOTA [18], IDF1 [19] and HOTA [20], are more common and reasonable evaluation metrics for the MOT task.

To sum up, ensemble methods used in the MOT task are still not well exploited. We summarize the reasons as following:

- MOT is a complex downstream task. The diversity and complexity of various tracking algorithms makes it difficult to design a general and effective ensemble algorithm.
- The tracking results are temporal sequences, not just classification scores or detection bounding boxes (bboxes). Therefore, intuitive methods like voting can’t be directly applied.
- The widely used metrics are instance-based. Compared with score-based metrics (e.g., mAP) in image classification and object detection, the instance-based metrics have no tolerance for redundant results, which introduces greater risk to ensemble methods.
In this paper, we propose a simple but effective ensemble method for instance-based metrics in the MOT task, called EnsembleMOT. It mixes tracking results from multiple trackers, and then merges them based on spatio-temporal constraints. The merged results may contain many redundant trajectories, so two post-processing methods, bbox-level length-based NMS and sequence-level length-based filtering, are applied to refine the results. Note that the proposed EnsembleMOT algorithm is model-independent and training-free, which gives it great flexibility in real applications. It doesn’t need the training/testing data, which just takes multiple tracking results as input, and then outputs the ensemble results with significant improvements.

We conduct experiments on the MOT17 dataset [21] with multiple state-of-the-art (SOTA) trackers as baseline, i.e., SiamMOT[2], CenterTrack[1], TransTrack[22], and FairMOT[5]. Results show that EnsembleMOT can improve metrics MOTA/IDF1/HOTA by 1 to 4. Moreover, it can be integrated with other post-processing algorithms, e.g., interpolation [4]. To the best of our knowledge, it is the first ensemble algorithm for MOT with instance-based metrics.

2. METHOD

2.1. Spatio-Temporal IoU

We utilize the spatio-temporal IoU (st-IoU) between trajectories as the constraints to merge them. The trajectory $T_i$ is represented as a sequence of bounding boxes:

$$T_i = \{b^t_i\}_{t=t_i^0}^{t_i^1},$$

where $b^t_i = [x^t_i, y^t_i, w^t_i, h^t_i]$ is the position of the bounding box of $T_i$ at frame $t$, and $t_i^0, t_i^1$ are the start-stop frame id.

Given two trajectories $\{T_i, t_i^0, t_i^1\}$ and $\{T_j, t_j^0, t_j^1\}$ with partial overlaps, i.e., $t_i^0 \leq t_j^0 \leq t_i^1 \leq t_j^1$, the frame-level spatial IoU is calculated at overlapping frames:

$$sIoU_{i,j} = \{IoU(b^t_i, b^t_j)\}_{t=t_i^0}^{t_i^1},$$

where $IoU(\cdot, \cdot)$ is the intersection-over-union between two bounding boxes.

Then the temporal intersection between $T_i$ and $T_j$ is

$$\text{inter}_{i,j} = |sIoU_{i,j}|,$$

and the temporal union is

$$\text{union}_{i,j} = t_j^1 - t_i^0.$$

Then, the st-IoU between $T_i$ and $T_j$ is calculated by

$$stIoU_{i,j} = \frac{\text{inter}_{i,j}}{\text{union}_{i,j}}.$$  

For those trajectories with no overlaps, the st-IoU is set to 0.

Considering that when the two trajectories have a large length gap, the st-IoU would be small even if the shorter one is completely covered. To solve this unreasonable case, we modify the denominator of Eq. (4) to the length of the shorter trajectory, i.e., $\text{union}_{i,j} = \min(t_j^1 - t_i^0, t_i^1 - t_j^0)$.

2.2. EnsembleMOT

The overall EnsembleMOT algorithm contains three steps, i.e., st-IoU-based mixture, bbox-level NMS and sequence-level filtering.
Algorithm 1 Merging procedure of EnsembleMOT

Input: Mixed multiple tracking results \( T = \{ T_i \}_{i=1}^N \), where
\( N \) is the number of trajectories and \( T_i \) is one trajectory
\( T_i = \{ t_i^{l=t_i} \}_{l=1}^{t_i} \); spatial threshold \( thr_s \); temporal threshold \( thr_t \).

Output: Ensemble tracking results \( T' = \{ T'_j \}_{j=1}^M \), where \( M \) is the number of resulting trajectories.

1. \( T \leftarrow sort(T, \text{key} = \text{len}) \)
2. \( \tilde{T} \leftarrow \emptyset \)
3. \( T' \leftarrow \emptyset \)
4. for \( T_i \) in \( T \) do
   5. if \( T_i \in \tilde{T} \) then
      6. continue
   7. end if
   8. \( \tilde{T} \leftarrow \emptyset \)
   9. for \( T_j \) in \( T \) and \( T_j \cdot \text{len} < T_i \cdot \text{len} \) do
      10. if \( T_j \in \tilde{T} \) then
          11. continue
      12. end if
      13. \( \text{stIoU}_{i,j} = \text{stIoU}(T_i, T_j, \text{thr}_s) \)
      14. if \( \text{stIoU}_{i,j} > \text{thr}_t \) then
          15. \( \tilde{T} \leftarrow \tilde{T} \cup \{ T_j \} \)
          16. \( T_{\text{merge}} \leftarrow \tilde{T} \)
      17. end if
   18. end for
   19. \( \hat{T}_i \leftarrow \text{merge}(\tilde{T}) \)
   20. \( T' \leftarrow T' \cup \{ \hat{T}_i \} \)
21. end for

In the st-IoU-based mixture step, we assume the longer trajectories tend to be more reliable like [16]. All trajectories are sorted in descending order of length, and then they are cycled through and compared with shorter trajectories. In each loop, given the longer trajectory \( T_i \), every shorter trajectory \( T_j \) that has a st-IoU \( \text{stIoU}_{i,j} \) larger than threshold \( \text{thr}_t \) with \( T_i \) is considered to be the same ID with \( T_i \). Therefore, they are merged into one trajectory. That is, for the overlapping frames, the final bboxes are the integration of corresponding bboxes from the two trajectories; for the non-overlapping frames, the final bboxes are from the one that appears at that frame. More details are listed in algorithm 1.

The merged results would contain a lot of redundant bboxes that belongs to the same object. To solve this problem, in the bbox-level NMS step, the non-maximum suppression with threshold \( \text{thr}_{\text{nms}} \) is applied to bboxes in each frame. The only difference between it and standard NMS is, the standard one uses confidence scores as the sorting criterion but the proposed method uses the length of trajectories.

In the followed sequence-level filtering step, trajectories shorter than \( \text{thr}_{\text{len}} \) is simply discarded to remove those inaccuracy caused by short trajectories.

2.3. Discussion

The proposed EnsembleMOT algorithm doesn’t need training process, codes of trackers or even datasets. It only takes multiple tracking results as input and outputs more accurate results, which brings great flexibility in applications.

Figure 1 shows example tracking results of CenterTrack [1], SiamMOT [2] and EnsembleMOT (CenterTrack + SiamMOT). Just bboxes of two objects (a woman and a man) are visualized for clarity. For CenterTrack, the woman (in green bbox) is well tracked, but the man has an ID switch. However, for SiamMOT, the man (in rufous bbox) is well tracked, but not for the woman. The third row presents the ensemble results of CenterTrack and SiamMOT, in which both the man and the woman are well tracked. In other words, the EnsembleMOT algorithm can obtain the best results of both trackers and produce more complete trajectories.

Strictly speaking, EnsembleMOT is an ensemble algorithm rather than an ensemble learning algorithm, because it doesn’t need learning. However, we hope that it can serve as a simple baseline and inspire more works on ensemble learning in MOT.

3. EXPERIMENTS

3.1. Datasets and Evaluation Metrics

Datasets. To verify the effectiveness of the proposed method, we conduct experiments on the MOT17 [21] datasets. MOT17 is a popular dataset for MOT, which consists of 7 sequences, 5,316 frames for training and 7 sequences, 5919 frames for testing. For ablation studies, recent works generally take the first half of each sequence in the MOT17 training set for training and the last half for validation. Following them, we conduct experiments on the validation set.

Metrics. We use the metrics MOTA, IDF1 and HOTA to evaluate tracking performance [18, 19, 20]. MOTA is computed based on FP, FN and IDs, and focuses more on detection performance. By comparison, IDF1 better measures the consistency of ID matching. HOTA is an explicit combination of detection score DetA and association score AssA, which balances the effects of performing accurate detection and association into a single unified metric.

3.2. Implementation Details

We select four recent SOTA trackers as our baseline methods, i.e., SiamMOT[2], CenterTrack[1], TransTrack[22], and FairMOT[5]. We run the official codes of these trackers with default settings to reproduce their results. For EnsembleMOT, in all experiments, we set spatial threshold \( \text{thr}_s = 0.5 \), temporal threshold \( \text{thr}_t = 0.5 \), NMS threshold \( \text{thr}_{\text{nms}} = 0.7 \) and length threshold \( \text{thr}_{\text{len}} = 20 \). For GSI, we use the default settings in [4].
Table 1. Results of applying EnsembleMOT and GSI on various SOTA trackers on the MOT17 dataset.

| Tracker(s)                  | EnsembleMOT | GSI | MOTA(↑) | IDF1(↑) | HOTA(↑) |
|----------------------------|--------------|-----|---------|---------|---------|
| SiamMOT [2]                |              |     | 62.32   | 67.35   | 56.52   |
| CenterTrack [1]            |              |     | 66.80   | 64.45   | 55.30   |
| TransTrack [22]            |              |     | 67.72   | 68.59   | 58.09   |
| FairMOT [5]                |              |     | 69.14   | 72.66   | 57.32   |
| FairMOT + SiamMOT          | ✓            | -   | 71.57 (+2.43) | 74.53 (+1.87) | 59.84 (+2.52) |
| FairMOT + TransTrack       | ✓            | ✓   | 71.25 (+2.11) | 74.67 (+2.01) | 60.82 (+2.73) |
| FairMOT + CenterTrack      | ✓            | ✓   | 72.59 (+3.45) | 75.23 (+2.57) | 61.06 (+3.74) |
| SiamMOT + CenterTrack      | ✓            | -   | 67.72 (+0.92) | 71.66 (+4.31) | 59.67 (+3.15) |
| TransTrack + CenterTrack   | ✓            | ✓   | 69.22 (+1.50) | 70.46 (+1.87) | 59.42 (+1.33) |
| SiamMOT + TransTrack       | ✓            | ✓   | 67.69 (-0.03) | 71.57 (+2.98) | 60.06 (+1.97) |

Table 2. Ablation results of different components of EnsembleMOT based on "SiamMOT+CenterTrack".

| Trackers                       | dropping | NMS | Filtering | MOTA(↑) | IDF1(↑) | HOTA(↑) |
|--------------------------------|----------|-----|-----------|---------|---------|---------|
| SiamMOT                        |          |     |           | 62.32   | 67.35   | 56.52   |
| CenterTrack                    |          |     |           | 66.80   | 64.45   | 55.30   |
| SiamMOT + CenterTrack          |          |     |           | 66.28   | 70.39   | 59.07   |
|                                | ✓        |     |           | 67.17   | 70.71   | 59.35   |
|                                | ✓        | ✓   |           | 67.73   | 70.84   | 59.38   |
|                                | ✓        | ✓   | ✓         | 67.72   | 71.66   | 59.67   |

3.3. Main Results

Table 1 presents the comparison between baseline trackers and our EnsembleMOT. It’s shown that EnsembleMOT can improve the metrics by a large margin. Moreover, it can also work in conjunction with the interpolation algorithm, GSI [4]. Specifically, compared with FairMOT, the ensemble results of “FairMOT+CenterTrack” improves its MOTA by 2.39, IDF1 by 1.75, HOTA by 2.65. By applying GSI, the improvements become 3.45, 2.57 and 3.74.

3.4. Ablations

Table 2 presents the ablation results of different components of EnsembleMOT. We use SiamMOT and CenterTrack as the basic trackers (in the first and second row). The baseline ensemble method in the third row only applies the merging procedure which utilizes the averaging bboxes from the two trajectories as the integrated bboxes in overlapping frames. The “dropping” means reserving the bbox from the longer trajectory and dropping other bboxes, rather than averaging them. This can reduce the cost of false merging. The “NMS” represents bbox-level NMS and “Filtering” represents sequence-level filtering. It is obvious that they can refine the detection and association results respectively.

4. CONCLUSION

In this paper, we propose a simple but effective ensemble algorithm for the MOT task, EnsembleMOT. It doesn’t need learning and has great flexibility in applications. Experiments demonstrate its effectiveness over four SOTA trackers. It can also work together with other post-processing methods, i.e., tracklets interpolation. We hope the proposed EnsembleMOT can serve as a simple baseline and inspire more ensemble works for MOT. In future work, we will exploit more general learning-based ensemble methods.

5. ACKNOWLEDGMENTS

This work is supported by Chinese National Natural Science Foundation under Grants (62076033, U1931202).
6. REFERENCES

[1] Xingyi Zhou, Vladlen Koltun, and Philipp Krähenbühl, “Tracking objects as points,” in European Conference on Computer Vision. Springer, 2020, pp. 474–490.

[2] Bing Shuai, Andrew Berneshawi, Xinyu Li, Davide Modolo, and Joseph Tighe, “Siammot: Siamese multi-object tracking,” in Proceedings of the IEEE/CVF conference on computer vision and pattern recognition, 2021, pp. 12372–12382.

[3] Nicolai Wojke, Alex Bewley, and Dietrich Paulus, “Simple online and realtime tracking with a deep association metric,” in 2017 IEEE international conference on image processing (ICIP). IEEE, 2017, pp. 3645–3649.

[4] Yunhao Du, Yang Song, Bo Yang, and Yanyun Zhao, “Strongsort: Make deepsort great again,” arXiv preprint arXiv:2202.13514, 2022.

[5] Yifu Zhang, Chunyu Wang, Xinggang Wang, Wenjun Zeng, and Wenyu Liu, “Fairmot: On the fairness of detection and re-identification in multiple object tracking,” International Journal of Computer Vision, vol. 129, no. 11, pp. 3069–3087, 2021.

[6] Omer Sagi and Lior Rokach, “Ensemble learning: A survey,” Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery, vol. 8, no. 4, pp. e1249, 2018.

[7] Bradley Efron, “Bootstrap methods: another look at the jackknife,” in Breakthroughs in statistics, pp. 569–593. Springer, 1992.

[8] Leo Breiman, “Bagging predictors,” Machine learning, vol. 24, no. 2, pp. 123–140, 1996.

[9] Robert E Schapire, “The strength of weak learnability,” Machine learning, vol. 5, no. 2, pp. 197–227, 1990.

[10] Leo Breiman, “Stacked regressions,” Machine learning, vol. 24, no. 1, pp. 49–64, 1996.

[11] Mitchell Wortsman, Gabriel Ilharco, Samir Ya Gadre, Rebeca Roelofs, Raphael Gontijo-Lopes, Ari S Marco, Hongseok Namkoong, Ali Farhadi, Yair Carmon, Simon Kornblith, et al., “Model soups: averaging weights of multiple fine-tuned models improves accuracy without increasing inference time,” in International Conference on Machine Learning. PMLR, 2022, pp. 23965–23998.

[12] Samuli Laine and Timo Aila, “Temporal ensembling for semi-supervised learning,” arXiv preprint arXiv:1610.02242, 2016.

[13] N Bodla, B Singh, R Chellappa, and LS Davis, “Improving object detection with one line of code. arxiv 2017,” arXiv preprint arXiv:1704.04503.

[14] Roman Solovyev, Weimin Wang, and Tatiana Gabruseva, “Weighted boxes fusion: Ensembling boxes from different object detection models,” Image and Vision Computing, vol. 107, pp. 104117, 2021.

[15] Jinlong Peng, Yueyang Gu, Yabiao Wang, Chengjie Wang, Jilin Li, and Feiuye Huang, “Dense scene multiple object tracking with box-plane matching,” in Proceedings of the 28th ACM International Conference on Multimedia, 2020, pp. 4615–4619.

[16] Yunhao Du, Junfeng Wan, Yanyun Zhao, Binyu Zhang, Zhihang Tong, and Junhao Dong, “Giaotracker: A comprehensive framework for mcmot with global information and optimizing strategies in visdrone 2021,” in Proceedings of the IEEE/CVF International Conference on Computer Vision, 2021, pp. 2809–2819.

[17] Olga Russakovsky, Jia Deng, Hao Su, Jonathan Krause, Sanjeev Satheesh, Sean Ma, Zhiheng Huang, Andrej Karpathy, Aditya Khosla, Michael Bernstein, Alexander C. Berg, and Li Fei-Fei, “ImageNet Large Scale Visual Recognition Challenge,” International Journal of Computer Vision (IJCV), vol. 115, no. 3, pp. 211–252, 2015.

[18] Keni Bernardin and Rainer Stiefelhagen, “Evaluating multiple object tracking performance: the clear mot metrics,” EURASIP Journal on Image and Video Processing, vol. 2008, pp. 1–10, 2008.

[19] Ergys Ristani, Francesco Solera, Roger Zou, Rita Cucchiara, and Carlo Tomasi, “Performance measures and a data set for multi-target, multi-camera tracking,” in European conference on computer vision. Springer, 2016, pp. 17–35.

[20] Jonathon Luiten, Aljosa Osep, Patrick Dendorfer, Philip Torr, Andreas Geiger, Laura Leal-Taixé, and Bastian Leibe, “Hota: A higher order metric for evaluating multi-object tracking,” International journal of computer vision, vol. 129, no. 2, pp. 548–578, 2021.

[21] Jonathon Luiten, Aljosa Osep, Patrick Dendorfer, Philip Torr, Andreas Geiger, Laura Leal-Taixé, and Bastian Leibe, “Hota: A higher order metric for evaluating multi-object tracking,” International journal of computer vision, vol. 129, no. 2, pp. 548–578, 2021.

[22] Peize Sun, Jinkun Cao, Yi Jiang, Rufeng Zhang, Enze Xie, Zehuan Yuan, Changhu Wang, and Ping Luo, “Transtrack: Multiple object tracking with transformer,” arXiv preprint arXiv:2012.15460, 2020.