
Multi-Camera Multi-Object Tracking and Re-Identification

Research Project

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Declaration

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Place, Date

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Abstract

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1 Introduction

1.1 Lorem ipsum

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2 Structure

2.1 Citations

2.1.1 General

[1]: Current Trends in MCMOT. State of the Art. A lot of basic and advanced knowledge. Good for introduction. Analyzes 30 MCT algorithms.

[2]: General description of multi-camera tracking. State of the Art, Markov Process, graph partition theory, tracking by joint constraints.

2.1.2 Real-time

[3]: Indoor scene, multiple top-view **fisheye** cameras. Possible to cover large space, less occlusion among objects. People detection and tracking. Calibrate cameras, real time (FPS of about 10) without GPU support.

[4]: Real-time distributed MCMOT system. City-scale scenario. Keeping communication and computing costs of each device low. Installs smart stations on the roadside and connects them to maintain communication. Decentralized Tracking. Kalman filter and hungarian algorithm. YoloX and DeepSORT.

2.1.3 VOT

[5]: VOT21 Challenge Results. Considers single-camera, single-target, model-free tracking. VOT-RT2021 focuses on real-time RGB tracking. Requires predicting bounding boxes. Top two trackers: TrasT_M and STARK_RT.

[6]: VOT22 Challenge Results. Considers single.camera, single-target. VOT-RT2022 focuses on real-time RGB tracking, VOT-RTs by segmentation, VOT-RTb by bounding boxes. Goes beyond previous challenges (updating datasets). Real-time tracking at 20fps. Top trackers: MS_AOT and OTrackSTB.

[7] VOTS23 Challenge Results. First year considering multiple-target tracking challenge. Explores short- and long-term at once. Only one challenge for all. Does not distinguish between these scenarios. Success is measured in IoU, tracking Quality

mathbf{Q}, Accuracy, Robustness, NRE, DRE, ADQ. Dataset with challenging situations, wide range and diverse set of objects, object which are a part of other objects. Also longer videos. 77 trackers submitted, 47 valid. Most trackers applied uniform dynamic model, utilized transformers, general segmentation network SAM. Top tracker: DMAOT built upon VOT22 winner AOT. Best segmentation-based trackers outperformed all bound.box trackers.

2.1.4 Dynamic Cameras

[8]: Single-Stage Global Association Approach. Dynamic MCMOT (moving cameras in vehicle). Solves fragment-tracking issues. Not relevant for static MCMOT.

2.1.5 Person Tracking

[9]: Non-overlapping cameras. Pedestrian Tracking. Fix ID-switching issues with long-term feature extraction. OC-SORT + feature extraction.

[10]: Soccer Players. Raw detection heat maps. Google Research Football Environment. Multi camera, multi targets. Cameras have fixed positions. Do not use bounding boxes, instead raw input with heat maps. Graph Neural Network. No visual cues, such as jersey numbers. Player movement trajectories and interaction between neighborhood players.

2.1.6 Vehicle Tracking (AI City)

[11]: Multi-camera vehicle tracking. No real-time tracking. Improve single-camera tracklets. 4th place in 2022 AI City Challenge. Track refinement module. Yolov5 pre-trained on COCO. Using GAN to generate synthetic data. Background filtering. Hierarchical clustering, zones, two rounds of clustering (tracklets separately each possible transition between cameras, akk tracks fro adjacent cameras).

[12]: Inspired [11]. First place in 2021 AI City Challenge. Yolov5 pre-trained on COCO. Most important: Introduces two step clustering (inter-zone, inter-camera clustering).

[13]: Fourth place in 2021 AI City Challenge (Track 3). Occlusion-aware tracking system. Inspired by Stadler.

[14]: Second place in 2022 AI City Challenge (Track 1). No new innovations made on first glance.

[15]: Graph Auto-Encoder and Self-Supervised Camera Link Model. First implementation of GAE in MTMCT. Very interesting paper. Network topology is learned automatically.

2.1.7 Re-ID

[16]: Proposes Mutual Information Temporal Weight Aggregated Person Re-ID Model (MI-TWA). Person re-identification. New algorithm. Not so interesting.

2.1.8 Misc

[17]: Tracking framework for multiple interacting targets both overlapping and non-overlapping cameras, raw target trajectory with group state. SVMS, homography-based voting schema, networkflow problem, K-shortest paths algorithm.

[18]: Non-overlapping multiple cameras tracking based on similarity function. Data association method. Similarity based on color appearance and camera topology. Use superpixels for extracting color features generated by Simple Linear Iterative Clustering K-means camera topology learning.

[19]: Mathematical multi-camera tracking approach. Pre-clustering obtained from 3D geometry projections.

[20]: Utilizes information regarding spatial and temporal consistency. Reconfigurable graph model. Two step approach: Associate all objects across cameras spatially then reconfig into a temporal graph model. Matching object across different views.

2.2 Approaches

Single vs Multi Camera Tracking

Static vs Dynamic MCMOT

Single-Stage vs Multi-Stage Tracking

Graph Neural Networks, Self-Attention, Transformers

Hierarchical Clustering

Tracking by detections vs Tracking by

Challenges: Occlusion, perspective changes, changes in lighting, changes in appearances, unknown number of targets in the whole network, unknown number of cameras in which a certain target appears.

Common Pipeline:

- Detection
- Feature Extraction
- Single Camera Tracking

- Cross Camera Association
- Multi Camera Tracking

2.3 Die Beschics

Single Object Detection (SOD)

Multi Object Detection (MOD)

Object Re-Identification (ReID)

Single Camera Tracking (SCT)

Multi Camera Tracking (MCT)

Camera Link Model (CLM)

Trajectories and Tracklets

Fisheye vs Normal Cameras

Different cameras have different technical characteristics.

Appearance features vs Motion features

2.4 Composition

- Introduction
- Motivation
- Technical Background
- Problem Statement
- State of the Art
- Approaches
- Challenges
- Papers
- Further Research
- Conclusion

2.5 Research

mentioned in [13]:

D. Stadler and J. Beyerer. Improving multiple pedestrian tracking by track management and occlusion handling. In IEEE Conf. Comput. Vis. Pattern Recog., 2021.

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Bibliography

- [1] T. I. Amosa, P. Sebastian, L. I. Izhar, *et al.*, “Multi-camera multi-object tracking: A review of current trends and future advances,” *Neurocomputing*, vol. 552, p. 126 558, 2023, ISSN: 0925-2312. DOI: <https://doi.org/10.1016/j.neucom.2023.126558>. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S0925231223006811>.
- [2] W. Tian, “Novel aggregated solutions for robust visual tracking in traffic scenarios,” Ph.D. dissertation, Karlsruher Institut für Technologie (KIT), 2019, 146 pp., ISBN: 978-3-7315-0915-8. DOI: 10.5445/KSP/1000091919.
- [3] T. Wang, C.-H. Liao, L.-H. Hsieh, A. W. Tsui, and H.-C. Huang, “People detection and tracking using a fisheye camera network,” in *2021 International Conference on Visual Communications and Image Processing (VCIP)*, Dec. 2021, pp. 1–5. DOI: 10.1109/VCIP53242.2021.9675451.
- [4] Y. Chen, L. Ma, S. Liu, M. Liu, C. Wu, and M. Li, “A real-time distributed multi-camera multi-object tracking system,” in *2022 2nd International Conference on Electrical Engineering and Mechatronics Technology (ICEEMT)*, Jul. 2022, pp. 146–149. DOI: 10.1109/ICEEMT56362.2022.9862731.
- [5] M. Kristan, J. Matas, A. Leonardis, *et al.*, “The ninth visual object tracking vot2021 challenge results,” in *2021 IEEE/CVF International Conference on Computer Vision Workshops (ICCVW)*, Oct. 2021, pp. 2711–2738. DOI: 10.1109/ICCVW54120.2021.00305.
- [6] M. Kristan, A. Leonardis, J. Matas, *et al.*, “The tenth visual object tracking vot2022 challenge results,” in *Computer Vision – ECCV 2022 Workshops*, L. Karlinsky, T. Michaeli, and K. Nishino, Eds., Cham: Springer Nature Switzerland, 2023, pp. 431–460, ISBN: 978-3-031-25085-9.
- [7] M. Kristan, J. Matas, M. Danelljan, *et al.*, “The first visual object tracking segmentation votes2023 challenge results,” in *Proceedings of the IEEE/CVF International Conference on Computer Vision (ICCV) Workshops*, Oct. 2023, pp. 1796–1818.
- [8] P. Nguyen, K. G. Quach, C. N. Duong, S. L. Phung, N. Le, and K. Luu, “Multi-camera multi-object tracking on the move via single-stage global association approach,” 2022. arXiv: 2211.09663 [cs.CV].

-
- [9] D.-J. Huang, P.-Y. Chou, B.-Z. Xie, and C.-H. Lin, “Multi-target multi-camera pedestrian tracking system for non-overlapping cameras,” in *2023 International Conference on Consumer Electronics - Taiwan (ICCE-Taiwan)*, Jul. 2023, pp. 629–630. DOI: 10.1109/ICCE-Taiwan58799.2023.10227006.
 - [10] J. Komorowski and G. Kurzejamski, “Graph-based multi-camera soccer player tracker,” in *2022 International Joint Conference on Neural Networks (IJCNN)*, Jul. 2022, pp. 1–8. DOI: 10.1109/IJCNN55064.2022.9892562.
 - [11] A. Specker, L. Florin, M. Cormier, and J. Beyerer, “Improving multi-target multi-camera tracking by track refinement and completion,” in *2022 IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW)*, Jun. 2022, pp. 3198–3208. DOI: 10.1109/CVPRW56347.2022.00361.
 - [12] C. Liu, Y. Zhang, H. Luo, *et al.*, “City-scale multi-camera vehicle tracking guided by crossroad zones,” in *2021 IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW)*, Jun. 2021, pp. 4124–4132. DOI: 10.1109/CVPRW53098.2021.00466.
 - [13] A. Specker, D. Stadler, L. Florin, and J. Beyerer, “An occlusion-aware multi-target multi-camera tracking system,” in *2021 IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW)*, Jun. 2021, pp. 4168–4177. DOI: 10.1109/CVPRW53098.2021.00471.
 - [14] F. Li, Z. Wang, D. Nie, *et al.*, “Multi-camera vehicle tracking system for ai city challenge 2022,” in *2022 IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW)*, Jun. 2022, pp. 3264–3272. DOI: 10.1109/CVPRW56347.2022.00369.
 - [15] H.-M. Hsu, Y. Wang, J. Cai, and J.-N. Hwang, “Multi-target multi-camera tracking of vehicles by graph auto-encoder and self-supervised camera link model,” in *2022 IEEE/CVF Winter Conference on Applications of Computer Vision Workshops (WACVW)*, Jan. 2022, pp. 489–499. DOI: 10.1109/WACVW54805.2022.00055.
 - [16] J. Li and Y. Piao, “Multi-target multi-camera tracking based on mutual information-temporal weight aggregation person re-identification,” in *2022 IEEE 5th International Conference on Electronic Information and Communication Technology (ICEICT)*, Aug. 2022, pp. 149–151. DOI: 10.1109/ICEICT55736.2022.9908659.
 - [17] S. Zhang, Y. Zhu, and A. Roy-Chowdhury, “Tracking multiple interacting targets in a camera network,” *Computer Vision and Image Understanding*, vol. 134, pp. 64–73, 2015, Image Understanding for Real-world Distributed Video Networks, ISSN: 1077-3142. DOI: <https://doi.org/10.1016/j.cviu.2015.01.002>. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S1077314215000168>.

- [18] H. Choi and M. Jeon, “Data association for non-overlapping multi-camera multi-object tracking based on similarity function,” in *2016 IEEE International Conference on Consumer Electronics-Asia (ICCE-Asia)*, Oct. 2016, pp. 1–4. DOI: 10.1109/ICCE-Asia.2016.7804834.
- [19] D. M. H. Nguyen, R. Henschel, B. Rosenhahn, D. Sonntag, and P. Swoboda, “Lmgp: Lifted multicut meets geometry projections for multi-camera multi-object tracking,” in *2022 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, Jun. 2022, pp. 8856–8865. DOI: 10.1109/CVPR52688.2022.00866.
- [20] C.-C. Cheng, M.-X. Qiu, C.-K. Chiang, and S.-H. Lai, “Rest: A reconfigurable spatial-temporal graph model for multi-camera multi-object tracking,” in *Proceedings of the IEEE/CVF International Conference on Computer Vision*, 2023, pp. 10 051–10 060. arXiv: 2308.13229 [cs.CV].