Multi-Target Multi-Camera Tracking and Re-Identification

from Detection to Tracking in Real-Time Scenarios

Research Project
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Declaration

I certify that I have written the submitted work independently. All passages taken verbatim or in spirit from the published or unpublished work of others, or from the author's own work, are marked as taken. All sources and tools used in the work are acknowledged. The work has not been submitted to any other examination authority with the same content or in substantial parts.

Place, Date

Signature

Abstract

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Contents

1 Introduction

Multi-Target Multi-Camera Tracking (MTMCT) is an essential field of research in computer vision, with significant applications ranging from video surveillance and traffic monitoring to sports analysis and crowd management. By simultaneously tracking multiple objects across various camera views, MTMCT systems aim to provide a comprehensive understanding of the scene dynamics and interactions.

The advent of deep learning and other advanced algorithms has revolutionized the field of MTMCT, especially in the last years, enabling faster, more accurate and reliable tracking in complex environments. In particular, online and real-time tracking methods have emerged as a critical area of focus, given their potential to provide timely and actionable insights in various real-world applications.

Even though Single-Target Single-Camera Tracking (ST-SCT) as well as Multi-Target Single-Camera Tracking (MT-SCT) has been extensively studied, MTMCT is still a relatively new and challenging, but also promising area of research. The complexity of MTMCT is significantly higher than ST-SCT and MT-SCT, due to the need to simultaneously track multiple objects across multiple cameras.

Single-Target Multi-Camera (ST-MCT) is a insignificant field of research, because if the use-case requires multiple cameras, it is almost always necessary to track multiple targets. Therefore, this project will not cover the special case of ST-MCT.

This research project aims to provide a comprehensive review of the state-of-the-art in MTMCT, with a special focus on online and real-time tracking methods. Latest trends, technologies, and challenges in this field are explored, drawing insights from recent research papers and studies. This review highlights the significant advancements made in MTMCT and identifies the gaps and opportunities for future research.

The rest of this project is structured as follows. Chapter 2 provides an overview of the key challenges and issues in MTMCT, along with a discussion of the datasets, metrics, and components of an MTMCT system. Futhermore it explains the basic concepts of object detection and tracking. Chapter 3 presents a detailed review of the literature on MTMCT, with the main focus on online and real-time tracking methods with static cameras, but also covering other approaches like offline tracking. Chapter 6 compares and contrasts the different methods reviewed in the previous sections, identifies the gaps and limitations in current research, and suggests areas for future research. While considering the ethical and privacy concerns related to MTMCT, it also discusses the need for regulations and guidelines. Finally, Chapter 7 concludes the project with a summary of the key findings and insights, along with stating the future directions and challenges for research in this area.

1.1 Definition of MTMCT

MTMCT is an integration of object detection and tracking methodologies to simultaneously track multiple predefined objects of interest across various camera views. The objective of MTMCT is to maintain a coherent understanding of the identities (IDs) of the objects and trajectories as they move through the fields of view of different cameras. The objects of interest are often people and vehicles, but in theory can be any moving object. The camera setup differs from one application to another, but typically consists of multiple cameras with either overlapping, non-overlapping, or partially overlapping fields of view. The cameras may be static or moving, and may be placed at different heights and angles. The cameras may also have differing technical specifications like resolution, frame rate, and field of view (FOV).

1.2 Importance of MTMCT

MTMCT plays a crucial role in various real-world applications. In video surveillance, it is used to monitor and analyze the movement of individuals or vehicles across different cameras, which can be vital for security and forensic analysis. In sports analysis, MTMCT can provide valuable insights by tracking the movement and interaction of players across different camera angles. In traffic monitoring, MTMCT can help manage traffic flow and detect incidents by tracking vehicles as they move through different camera views.

Furthermore, the need for online and real-time tracking in these applications is imperative. Real-time processing of data streams from multiple cameras and providing instantaneous tracking results are essential to make timely and actionable insights, which is particularly relevant in scenarios like accident prevention, control of traffic flow, crime detection, and real-time sports analysis.

1.3 Objective of Research Project

First, the basics concepts of SCT are explained to provide a foundation for understanding MTMCT. The primary objective of this project is to provide a comprehensive overview of proposed methods and technologies for MTMCT and review the current state-of-the-art in MTMCT, with a special focus on online and real-time tracking methods. Through an extensive literature review, the aim is to explore the latest trends, technologies, and challenges faced in this field, and provide insights drawn from recent research papers and studies. By highlighting the significant advancements made in MTMCT, the intend is to identify the gaps in current research and outline potential avenues for future exploration, while keeping in mind the ethical and privacy concerns related to MTMCT.

1.4 Related Work

Back in 1999 and 2001 Cai and Aggarwal [1] and Chang and Gong [2] conducted research in the area of tracking people in an multi-camera system. Also in 2001, Khan, Javed, and Shah [3] proposed a method for tracking people and vehicles with uncalibrated cameras. The system is able to discover spatial relationships between the FOVs of the three cameras used. All three works rely on Bayesian classification and networks.

The methods even demonstrated the feasibility of tracking people in real-time, but are in general very limited in their capabilities. For example the work of Chang and Gong is limited to people in upright pose. The algorithm proposed by Cai and Aggarwal lacks robustness compared to the single-camera tracking and Khan, Javed, and Shah approach does not calibrate the cameras correctly and is highly susceptible to errors caused by occlusion. But since then the field of tracking in multi-camera systems has evolved significantly in the past two decades.

The doctoral thesis of Tang, Naphade, Liu, *et al.* [4, Chapter 5], published in 2019, revolves around the topic of tracking multiple objects and gives a state-of-the-art overview of this field. It does not cover the topic of multi-camera tracking. However, it provides a mathematical insight into the topic of tracking multiple objects.

The most recent and comprehensive review of MTMCT was published in 2023 by Amosa, Sebastian, Izhar, *et al.* [5]. It provides a detailed overview of the state-of-the-art in MTMCT, covering the latest trends, technologies, and challenges in this field. However, the mentioned review gives a broader overview and does not focus on online and real-time tracking methods, which is the main focus of this project. Futhermore, this research project aims to provide an easier introduction to the field of MTMCT by first explaining the basics before diving into the details of the latest research.

2 Background

This chapter provides an overview of the basic concepts of object detection and tracking and the steps of an Multi-Target Multi-Camera Tracking (MTMCT) system, along with a discussion of its key challenges and issues. Also the foundational building blocks of MTMCT are introduced, namely Single-Target Single-Camera Tracking (ST-SCT) and Multi-Target Single-Camera Tracking (MT-SCT). Futhermore it explains the datasets and metrics used to evaluate MTMCT systems.

2.1 Steps of an MTMCT System

An MTMCT system typically consists of the following steps: detection, feature extraction, data association, and tracking. Only the basic and fundamental concepts are explained in this section, more advanced and recent methods, mostly revolving around deep learning, will be discussed in chapter 3.

2.1.1 Detection

Detection refers to the process of identifying objects of interest within video frames. This is typically done using a variety of techniques, ranging from traditional image processing methods to deep learning models. The objective of the detection step is to locate and classify objects in the frame, providing a basis for subsequent steps in the MTMCT process.

Commonly used object detection frameworks in the context of MTMCT are Faster R-CNN [6], YOLO [7], and SSD [8]. These frameworks are typically trained on large datasets (see section 2.4) to detect a wide range of objects.

2.1.2 Feature Extraction

Feature extraction involves extracting relevant information from detected objects to facilitate tracking. This could include low-level features like color, shape and texture as well as high-level features like object parts and their spatial relationships, speed, and direction of movement. The features extracted from objects are used to identify and distinguish them from other objects in the scene.

Fundamental feature extraction methods are Histogram of Oriented Gradients (HOG) [9] and Scale-Invariant Feature Transform (SIFT) [10].

2.1.3 Data Association

Data association is the process of associating detected objects across different frames and camera views. This step is crucial in maintaining the IDs of objects as they move through the scene or even leaving and re-entering the scene, which is called re-identification (re-ID).

The data association step is a huge research field in MTMCT and various methods have been proposed to solve this problem. Most methods are based on the Hungarian algorithm [11] and the Kalman filter [12], which were proposed in the 1960s by Harold Kuhn and Rudolf Kalman respectively.

2.1.4 Tracking

Tracking refers to the step of maintaining the trajectory of detected objects over time. This involves predicting the future location of an object based on its past movements and updating its trajectory as new observations, so the next frame of a video, become available.

Various tracking algorithms can be employed for this purpose, ranging from simple methods like frame-to-frame matching to more sophisticated approaches like Multiple Hypothesis Tracking (MHT) [13] and Joint Probabilistic Data Association (JPDA) [14].

2.2 Fundamental Concepts

This section briefly describes the preliminary concepts of MTMCT, which are essential to follow the progression from basic object tracking methods to advanced MTMCT techniques.

2.2.1 Single-Target Single-Camera Tracking (ST-SCT)

ST-SCT is the simplest form of object tracking and involves tracking a single target in the field of view of a single camera. The primary goal of ST-SCT is to maintain the identity (ID) and trajectory of the target as it moves through the view of the camera.

2.2.2 Multi-Target Single-Camera Tracking (MT-SCT)

MT-SCT builds upon the principles of ST-SCT but introduces the added complexity of dealing with multiple targets in a view of a single-camera. It aims to track multiple objects simultaneously while maintaining the ID of each target and avoiding ID switches. This requires sophisticated algorithms that can handle occlusions, interactions between targets, and other challenges that especially arise in crowded scenes.

The progression from ST-SCT to MT-SCT, and ultimately to MTMCT, reflects the increasing complexity and capability of tracking systems to handle more complex scenarios. This evolution is possible, due to advances in computer vision and machine learning, which provide the tools necessary to tackle the challenges associated with tracking multiple targets across multiple camera views.

2.3 Challenges and Issues

The process of tracking multiple objects across various camera views requires careful consideration of various factors that can significantly affect the performance and accuracy of the tracking system. Some of the main challenges and issues faced in MTMCT are discussed in the following sections.

2.3.1 Occlusion

Occlusion occurs when an object is partially or completely blocked from view, making it difficult to accurately track its position and identity. This can happen when objects overlap with each other or are obstructed by other elements in the scene, such as buildings or trees. Occlusion is a common challenge in crowded environments, such as public spaces and sporting events, where multiple objects are often in close proximity to each other.

2.3.2 Varying Lighting Conditions

Lighting conditions can have a significant impact on the performance of an MTMCT system. Variations in lighting, such as changes in natural light throughout the day or artificial lighting when a tracked object enters a building, can affect the appearance of objects and make it challenging to maintain consistent tracking. The presence of shadows and reflections can also complicate the tracking process.

2.3.3 Camera Specifications

The specifications of the cameras used in an MTMCT system can have a significant impact on its performance. When multiple cameras are used, they may have different:

- Resolution: The number of pixels in the image
- Frame rate: The number of frames captured per second
- Field of view (FOV): The area captured by the camera
- Angle: The angle from which the camera captures the scene

This can make it challenging to maintain consistent tracking across different camera views, especially when objects move from one camera to another. Objects may appear differently when viewed from different cameras, and their size and shape can be distorted. Achieving accurate tracking requires the system to account for these variations and correctly align objects across different camera views.

2.4 Datasets and Challenges

Datasets are a fundamental aspect of MTMCT research, they are the resource for the training, evaluation, and comparison of various tracking methods. A diverse array of datasets exists to fullfil requirements of MTMCT research, each offering unique challenges and scenarios.

Commonly utilized datasets to train object detectors are:

- **Microsoft COCO** (Common Objects in Context) [15]: Comprehensive dataset utilized for object detection, segmentation, and captioning. COCO comprises a diverse range of objects.
- **ImageNet** [16]: Vast dataset employed for image classification and object detection. Object detectors trained on ImageNet are able to recognize an broad range of objects.

However, MTMCT research typically revolves around tracking specific object classes, predominantly people and vehicles. The following datasets are more fitting for this purpose:

- **PETS2009** (Performance Evaluation of Tracking and Surveillance) [17]: Focuses on people tracking and surveillance. PETS2009 has a large variety of scenarios, including crowd monitoring and abnormal behavior detection, making it ideal for developing and testing tracking algorithms in complex, dynamic environments.

- **DukeMTMC**[18]: Multi-target, multi-camera dataset specifically created for person re-identification and tracking. It offers a comprehensive view of a diverse urban environment. with rich annotations and challenging scenarios, DukeMTMC serves as one of the most important resource for advancing MTMCT research.

In recent years, challenges have been established to encourage research in object tracking, although they have mostly centered on ST-SCT and MT-SCT. Nevertheless, these challenges remain relevant to MTMCT research. The primary challenges are:

- **MOTChallenge** [19]: Benchmark dataset specifically designed for MTMCT. It includes crowded environments, variable lighting conditions, and camera movements. Moreover, it provides ground truth data to facilitate evaluation.
- **AICity Challenge** [20]: Focuses on AI applications in smart cities and includes multi-object tracking for traffic surveillance and anomaly detection as one of its key components.
- **VOT Challenge** (Visual Object Tracking Challenge) [21]: An annual competition that provides a standardized dataset and evaluation framework for single-object tracking.
- **VOTS Challenge** (Visual Object Tracking and Segmentation Challenge) [22]: An extension of the VOT Challenge that focuses on multi-object tracking. The challenge, recently published in October 2023, affirms the quickly growing interest in this field.

Table 2.1 provides quick overview of relevant datasets, challenges and benchmarks available for MTMCT research, along with their key characteristics and references.

Table 2.1: Overview of Datasets and Challenges [5, Tab. 2]

Name	**Cameras**	**Length**	**Challenges**	**Annotations**	**Scenarios**
PETS [17]	7+	Varies	Occlusion, Lighting	Yes	Indoor, Outdoor
DUKE [18]	8	85 minutes	Occlusion, Identity Switch	Yes	Campus Environment
AICITYChallenge [20]	20+	Varies	Occlusion, Scale Variation	Yes	Urban Traffic
VOTChallenge [21]	60	Varies	Occlusion, Illumination Changes	Yes	Multiple
VOTSChallenge [22]	10+	Varies	Occlusion, Background Clutter	Yes	Multiple
MOTChallenge [19]	6+	Varies	Occlusion, Scale Variation	Yes	Urban Environment

2.5 Metrics and Evaluation

2.5.1 MOTA

2.5.2 MOTP

2.5.3 IDF1

2.5.4 MT

3 Literature Review

Provide an overview of the main methods used in MTMCT

3.1 Methods

3.1.1 Tracking-by-Detection

3.1.2 Single-Object Tracking

3.1.3 Multi-Object Tracking

3.1.4 Single-Camera Tracking

3.1.5 Multi-Camera Tracking

3.1.6 Re-Identification

3.2 Trends

Discuss the trends and advancements in MTMCT

3.2.1 Deep Learning

3.2.2 Graph Neural Networks

3.2.3 Edge Computing

3.3 Strengths and Weaknesses

4 Online and Real-Time Tracking

4.1 Significance and Benefits

Explain the significance of online and real-time tracking in MTMCT and its benefits over offline tracking methods.

4.2 Algorithms and Technologies

Review the latest algorithms and technologies used for online and real-time tracking, such as Siamese networks, deep reinforcement learning, and edge computing.

4.3 Challenges and Limitations

Discuss the challenges specific to online and real-time tracking, such as handling large data streams and ensuring low latency.

Evaluate the performance and limitations of existing online and real-time tracking systems.

5 Other Methods

Briefly review other methods used in MTMCT, such as offline tracking, semi-supervised tracking, and unsupervised tracking. Compare and contrast these methods with online and real-time tracking. Highlight the scenarios where these methods may be more suitable or beneficial.

6 Discussion

6.1 Comparison of Methods

Compare and contrast the different methods reviewed in the previous chapters.

6.2 Gaps and Limitations

Identify the gaps and limitations in current research.

6.3 Future Research

Suggest areas for future research.

6.4 Ethical and Privacy Concerns

Discuss the ethical and privacy concerns related to MTMCT and the need for regulations and guidelines.

7 Conclusion

7.1 Summary

Summarize the main points made in your paper.

Highlight the importance of online and real-time tracking in MTMCT and its potential to revolutionize various applications.

7.2 Future Directions

Conclude by stating the future directions and challenges for research in this area.

8 Structure

8.1 Citations

8.1.1 General

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

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

[3]: Tracking people in multiple uncalibrated cameras. Discover spatial relationships between the camera FOVs. Tested on PETS 2001.

8.1.2 Beginning

[1]: First approaches of tracking humans in multi camera network. Already done in 1999 with real-time tracking. Automatic camera switching. Bayesian classification schema.

[2]: Bayesian modality fusion to track multiple people in an indoor environment. Tries to fix already known occlusion problem.

8.1.3 Real-time

[6]: Faster R-CNN. Towards Real-Time Object Detection. Region Proposal Network (RPN). RPN is trained end-to-end. Attention mechanism. 5-17 fps on GPU. Two modules (first region proposal, second detector). Sharing convolutional features.

[24]: Toward Real-Time. Only multi-object tracking. Introduces JDE (Joint learning of detection and embedding). Very important paper (first real-time MOT system). Single-shot detector

[25]: 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.

[26]: 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.

[27]: FairMOT, one-shot tracker (anchor-free style). Tackles issue of object detection against re-ID. Re-ID often threated as secondary task. Reasons behind failure: anchors, feature sharing, feature dimension.

[28]: Multiple non-overlapping cameras using fast-constrained dominant set clustering (FCDSC). Three-layer hierarchical approach. Orders of magnitudes faster than existing methods. Can be used in conjunction with re-id algorithms. Good graphics in paper.

8.1.4 VOT

[29]: 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.

[21]: 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 OSTrackSTB.

[22] 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 mathbfQ, 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.

8.1.5 Dynamic Cameras

[30]: Tracking multiple vehicles in the front view of an onboard monocular camera. Siamese network with a spatial pyramid pooling. Markov decision process. Effective for real-time long-term tracking. Hungarian algorithm, reinforcement learning.

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

8.1.6 Person Tracking

[32]: Integrating social grouping behavior for tracking pedestrians. Online learned conditional random field (CRF). Non-overlapping cameras.

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

[34]: 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.

[35]: Optical-based Pose Association (OPA). Online data association algorithm. Solve the occlusion problem. Take also human pose (see [36]) and optical flow into account, not only visual and spatial information. OpenPose, Object Keypoint Similarity, PWC-Net, Kunh-Munkras algorithm.

8.1.7 Vehicle Tracking (AI City)

[37]: 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).

[38]: Inspired [37]. First place in 2021 AI City Challenge. Yolov5 pre-trained on COCO. Most important: Introduces two step clustering (inter-zone, inter-camera clustering).

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

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

[41]: First place in 2020 AI City Challenge (Track 3). Electricity. Efficient vehicle tracking system. Aggregation loss and fast multi-target cross-camera tracking strategy. Weighted inter-class non-maximum suppression.

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

8.1.8 Re-ID, Data Association and Tracklet Matching

[43]: Unsupervised cross-dataset transfer learning for person re-id. Unsupervised multi-task dictionary learning (UMDL) model. Uses latent attributes. Asymmetric multi-task learning approach.

[44]: First time use of hierarchical clustering for person re-id. No online method (needs neighboring frames).

[45]: Online-learning-based person re-id. Fully unsupervised learning method. Systematically builds camera link model. Two-way GMM fitting. Multi-kernel adaptive segmentation. Multi-shot framework.

[46]: Orientation-driven person re-id (ODPR). Leverages the orientation cuest and stable torso features to learn a discriminative representation. Also estimates camera topology.Entry/Exit zones are clustered with GMM.

[47]: Locality aware appearance metric (LAAM). Intra- and inter-camera metric for re-ID. Can be applied on top of globally learned re-ID features. Improves tracking accuracy.

[36]: State-aware Re-ID. Human pose information is adopted to infer the target state including occlusion status and orientation. State-of-the-art result on Duke-MTMCT.

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

[49]: Dynamic Graph Model with Link Prediction. Tackles problem of data association with a dynamic graph model. Better feature representations and able to recover from lost tracks during camera transitions. Works for person and vehicle tracking for overlapping and non-overlapping cameras. First time link prediction and dynamic graph are used together for MCMOT. Attention models.

[50]: Metadata-Aided Re-ID. Uses metadata information (car type, brand and color) for re-ID. Traffic-aware single-camera tracking. trajectory-based camera link model. Not so interesting.

[51]: Tracklet-to-Target Assignment. Solves cross-camera tracklet matching problem by TRACTA. Proposes the Restricted Non-negative Matrix Factorization (RNMF) algorithm. Estimates the number of targets in the whole network. Important paper.

8.1.9 Datasets

[18]: Largest annotated calibrated data set for MTMC (DukeMTMC).

[52]: Created MTMCT dataset in GTA V. No privacy issues. 6 cameras over 100 minutes per camera. Largest synthetic dataset for multi camera multi person tracking.

8.1.10 Misc

[53]: 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.

[54]: 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.

[55]: Multiple hypothesis tracking (MHT) for multi-camera tracking. Track hypothesis trees. Disjoint views. Status: tracking, searching, end-of-track. Real-time online method (15 fps). Also uses pose of person.

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

[57]: 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.

[58]: Equalized Global Graph Model-Based Approach. Improved similarity metric for single- and multiple-camera tracking. SCT and ICT in one step.

[59]: Joint person re-id and camera network topology inference. First framework which jointly solves both problems. Minimal prior knowledge about environment. Multi-shot method implemented as random-forest.

[60]: Joint learning of feature, affinity and multi-dimensional assignment (FAMNet). Online MOT. One deep-network for all three tasks. End-to-end learning.

8.2 Approaches

Single vs Multi Camera Tracking

Static vs Dynamic MCMOT

Single-Stage vs Multi-Stage Tracking

Intra camera vs Inter camera tracking

Local and Global tracklets

Cross-camera tracklet matching problem

Graph Neural Networks, Self-Attention, Transformers

Hierarchical Clustering

Gaussian Mixture Models (GMM)

Tracking by detections (Multi-shot) vs One-shot (Single-shot)

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

8.3 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

Online vs Offline Tracking (Online: real-time and frame-by-frame, Offline: post-processing)

Local neighborhood: Single-camera tracking: Consecutive frames. Multi-camera tracking: Neighboring cameras.

Different cameras have different technical characteristics.

Appearance features vs Motion features

Datasets:

- DukeMTMC
- MOTChallenge

- AI City Challenge
- PETS
- CityFlow

8.4 Composition

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

8.5 Research

8.6 Mentioned Papers

mentioned in [39]:

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

mentioned in [55]:

Ristani, E., Tomasi, C.: Tracking multiple people online and in real time. Proc. Asian Conf. Computer Vision, Singapore, 2014, pp. 444-459

Wei, S.-E., Ramakrishna, V., Kanade, T., et al.: Convolutional pose machines. Proc. IEEE Conf. Computer Vision and Pattern Recognition, Las Vegas, USA, 2016, pp. 4724-4732

mentioned in [44]:

Kuhn, H. W. 2010. The hungarian method for the as- signment problem. In 50 Years of Integer Programming.

Zhang, X.; Luo, H.; Fan, X.; Xiang, W.; Sun, Y.; Xiao, Q.; Jiang, W.; Zhang, C.; and Sun, J. 2017. Aligne-dreid: Surpassing human-level performance in person re-identification. arXiv preprint arXiv:1711.08184.

Zhong, Z.; Zheng, L.; Cao, D.; and Li, S. 2017. Re- ranking person re-identification with k-reciprocal encod- ing. 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR) 3652-3661.

mentioned in [58]:

S. Yu, Y. Yang, and A. Hauptmann, "Harry Potters Marauders Map: Localizing and tracking multiple persons-of-interest by nonnegative dis- cretization," in Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR), Jun. 2013, pp. 3714-3720.

mentioned in [32]:

X. Chen, K. Huang, and T. Tan, "Object tracking across non-overlapping views by learning inter-camera transfer models," Pattern Recognit., vol. 47, no. 3, pp. 1126-1137, 2014.

E. Reinhard, M. Adhikhmin, B. Gooch, and P. Shirley, "Color transfer between images," IEEE Comput. Graph. Appl., vol. 21, no. 5, pp. 34-41, Sep./Oct. 2001.

M. Moussaiid, N. Perozo, S. Garnier, D. Helbing, and G. Theraulaz, The walking behaviour of pedestrian social groups and its impact on crowd dynamics

W. Ge, R. T. Collins, and R. B. Ruback, "Vision-based analysis of small groups in pedestrian crowds," IEEE Trans. Pattern Anal. Mach. Intell., vol. 34, no. 5, pp. 1003-1016, May 2012.

D. Helbing and P. Molnar, Social force model for pedestrian dynamics, Phys. Rev. E, vol. 51, pp. 4282-4286, May 1995.

8.6.1 Arising Questions

Online Tracking?

Hungarian algorithm?

Multi Object vs Multi Target (definitions)

Attention mechanisms

Detection Frameworks:

- YOLO
- Faster R-CNN

- R-CNN

Tracking Frameworks:

- OpenCV
- DeepSORT
- SORT
- MOTSA

List of Figures

List of Tables

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