

MTMCT

Multi-Target Multi-Camera Tracking and Re-Identification
from Detection to Tracking in Real-Time Scenarios

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Introduction

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Introduction

MTMCT

- Object detection and tracking across multiple cameras

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- Maintain global IDs of targets (re-ID)

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 - **Video Surveillance:** Monitor public places,
e.g. airports, train stations, ...

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 - **Video Surveillance:** Monitor public places,
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- Important area in computer vision with many applications:
 - **Video Surveillance:** Monitor public places,
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 - **Traffic Monitoring:** Monitor traffic,
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 - **Sports Analysis:** Analyse sport events,
e.g. football, basketball, ...

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- Important area in computer vision with many applications:
 - **Video Surveillance:** Monitor public places,
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 - **Traffic Monitoring:** Monitor traffic,
e.g. highways, intersections, parking lots, ...
 - **Sports Analysis:** Analyse sport events,
e.g. football, basketball, ...
 - **Crowd Management:** Analyse crowd behavior,
e.g. demonstrations, concerts, ...
 - ...

Introduction

Objectives

- Literature review

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- Focus on online and real-time tracking methods

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- Discuss evolution (traditional → deep learning)

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- Focus on online and real-time tracking methods
- Explain background and fundamentals
- Discuss evolution (traditional → deep learning)
- Identify:
 - Research gaps
 - Potential improvements
 - Future directions

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- Literature review
- Focus on online and real-time tracking methods
- Explain background and fundamentals
- Discuss evolution (traditional → deep learning)
- Identify:
 - Research gaps
 - Potential improvements
 - Future directions
- Consider ethical and privacy aspects

Background

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- Steps of MTMCT
- Intra- vs. Inter-Camera Tracking
- Tracking Process
- Fundamental Concepts
- Challenges in MTMCT
- Metrics and Evaluation

3 Literature Review

4 Discussion

Background

Steps of MTMCT

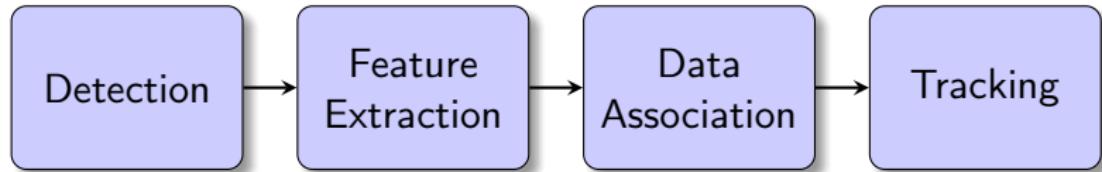


Figure: Steps of an MTMCT System

Background

Steps of MTMCT

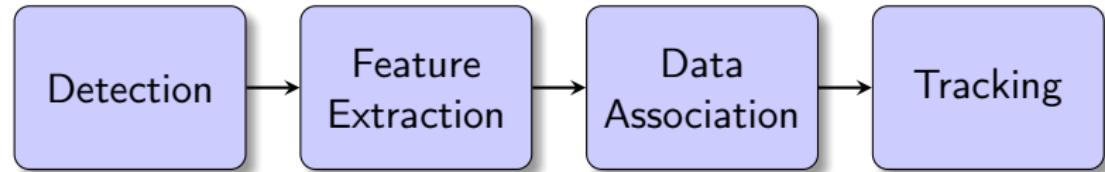


Figure: Steps of an MTMCT System

- **Detection:** Detect objects in each frame of each camera

Background

Steps of MTMCT

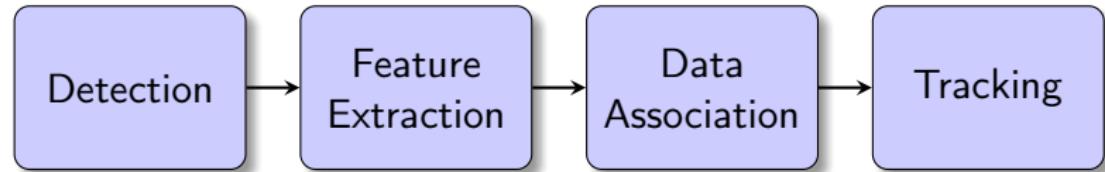


Figure: Steps of an MTMCT System

- **Detection:** Detect objects in each frame of each camera
- **Feature Extraction:** Extract features from each detection

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Steps of MTMCT

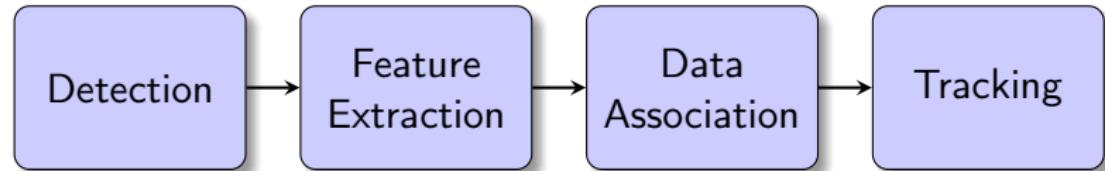


Figure: Steps of an MTMCT System

- **Detection:** Detect objects in each frame of each camera
- **Feature Extraction:** Extract features from each detection
- **Data Association:** Associate detections with existing trajectories
 - **Intra-Camera:** Within each camera
 - **Inter-Camera:** Across cameras

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Steps of MTMCT

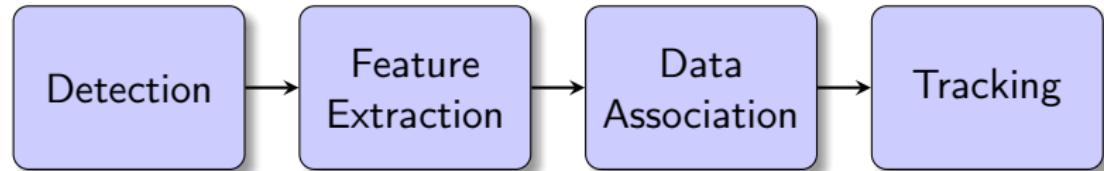


Figure: Steps of an MTMCT System

- **Detection:** Detect objects in each frame of each camera
- **Feature Extraction:** Extract features from each detection
- **Data Association:** Associate detections with existing trajectories
 - **Intra-Camera:** Within each camera
 - **Inter-Camera:** Across cameras
- **Tracking:** Maintaining trajectories over time
(create, update, delete)

Background

Intra- vs. Inter-Camera Tracking

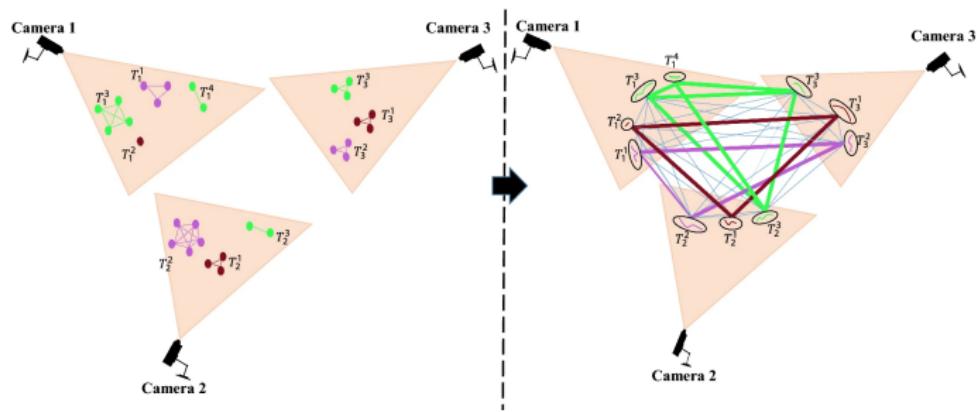


Figure: Intra- (left) and Inter-Camera (right) Tracking [1, Fig. 1]

Background

Tracking Process

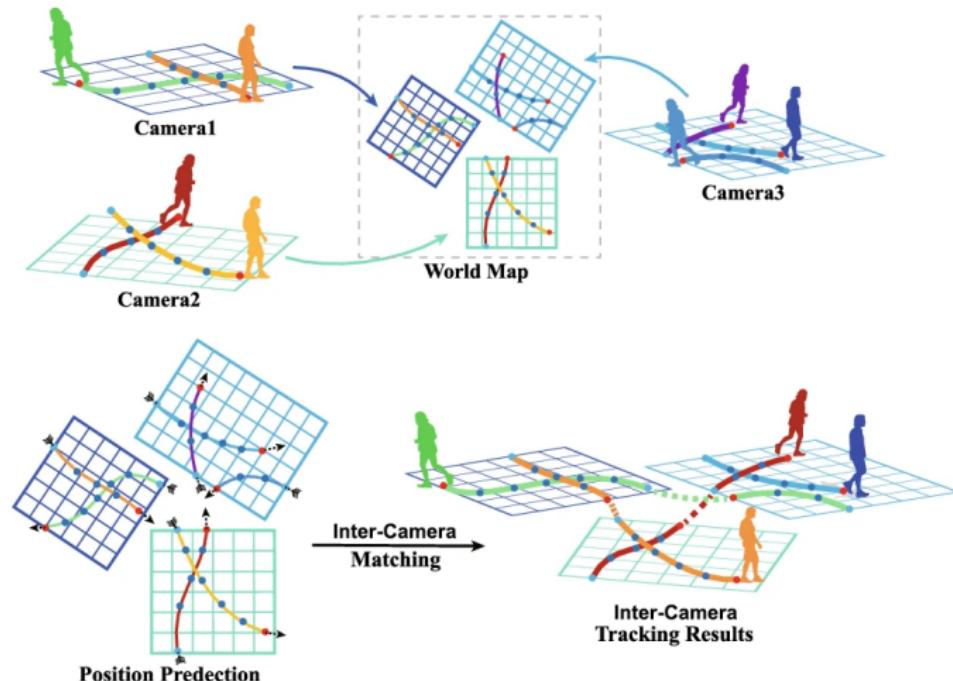


Figure: Tracking Process [2, Fig. 1]

Background

Fundamental Concepts

- Single-Target Single-Camera Tracking (STSCT)
 - Simplest form of tracking
 - Track a single target in FOV of a single camera
 - **Goal:** Maintain ID and trajectory of target

Background

Fundamental Concepts

- Single-Target Single-Camera Tracking (STSCT)
 - Simplest form of tracking
 - Track a single target in FOV of a single camera
 - **Goal:** Maintain ID and trajectory of target
- Multi-Target Single-Camera Tracking (MTSCT)
 - Builds on principles of STSCT
 - Adds complexity of multiple targets
 - **Goal:** Maintain IDs and trajectories of targets, avoid ID switches

Background

Challenges in MTMCT

- **Occlusions:** Targets can be occluded by other targets or objects

Background

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- **Varying Lighting Conditions:** Lighting conditions can change over time and across cameras

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Challenges in MTMCT

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- **Camera Specifications:** Cameras can have different specifications (e.g. resolution, FPS, FOV, angle, ...)

Background

Challenges in MTMCT

- **Occlusions:** Targets can be occluded by other targets or objects
- **Varying Lighting Conditions:** Lighting conditions can change over time and across cameras
- **Camera Specifications:** Cameras can have different specifications (e.g. resolution, FPS, FOV, angle, ...)
- **Uncertainties (unknown number of):**
 - Targets in entire camera
 - Targets in single camera
 - Cameras a tracked target appears

Background

Metrics and Evaluation

- **MOTP:** Multiple Object Tracking Precision
(accuracy of object localization) [3]
- **MOTA:** Multiple Object Tracking Accuracy
(three in one: misses, false positives, ID switches) [3]

Background

Metrics and Evaluation

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- **IDF1:** ID F1 Score (harmonic mean of precision and recall) [4]

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Metrics and Evaluation

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(three in one: misses, false positives, ID switches) [3]
- **IDF1:** ID F1 Score (harmonic mean of precision and recall) [4]
- **MT:** Mostly Tracked ($\geq 80\%$ correctly tracked) [5]
- **ML:** Mostly Lost ($\leq 20\%$ correctly tracked) [5]

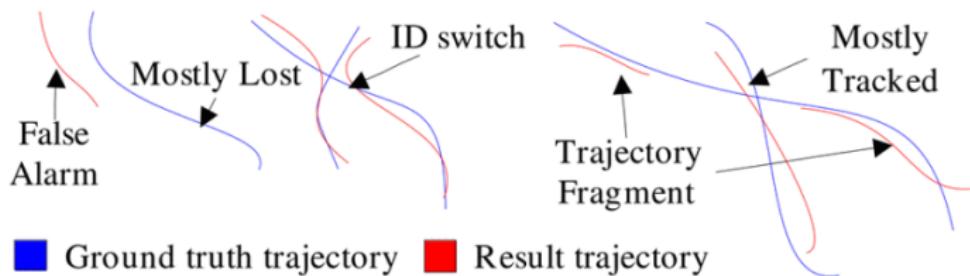


Figure: MT and ML [source image: 5, Fig. 5]

Literature Review

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- Tracking Paradigms
- Graph-Based
- Edge-Computing
- Online and Real-Time
- State-of-the-Art
- Honorable Mentions

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Literature Review

Milestones

- Detection

Literature Review

Milestones

- Detection

- (Faster) R-CNN [6]–[8]
- YOLO [9]
- SSD [10]
- ...

Literature Review

Milestones

- Detection
- Feature Extraction

Literature Review

Milestones

- Detection
- Feature Extraction
 - Scale-Invariant Feature Transform (SIFT) [11]
 - Histogram of Oriented Gradients (HOG) [12]
 - CNNs [13]
 - ...

Literature Review

Milestones

- Detection
- Feature Extraction
- Data Association

Literature Review

Milestones

- Detection
- Feature Extraction
- Data Association
 - Hungarian Algorithm [14]
 - Joint Probabilistic Data Association Filters (JPDAF) [15]
 - Probabilistic Occupancy Map (POM) [16]
 - RNNs [17]
 - ...

Literature Review

Milestones

- Detection
- Feature Extraction
- Data Association
- Tracking

Literature Review

Milestones

- Detection
- Feature Extraction
- Data Association
- Tracking
 - Kalman Filter [18]
 - Multiple Hypothesis Tracking (MHT) [19]
 - ...

Literature Review

Milestones

- Detection
- Feature Extraction
- Data Association
- Tracking
- Datasets and Challenges

Literature Review

Milestones

- Detection
- Feature Extraction
- Data Association
- Tracking
- Datasets and Challenges
 - see Table 1

Literature Review

Milestones - Datasets and Challenges

Table: Overview of Datasets

Dataset	Environment	Num. of Scenarios	Num. of Cameras (Overlap)	FPS	IDs	Year	Class
PETS [20]	Outdoor	3	8 (✓)	25	—	2009	Person
MARS [21]	Mixed	Multiple	6 (✓)	—	1261	2016	Person
MOT16 [22]	Outdoor	14	1	25-30	—	2016	Person, Vehicle
DukeMTMC [4]	Outdoor	1	8 (✓)	60	2834	2016	Person
MOT17 [22]	Outdoor	14	1	25-30	—	2018	Person
Wildtrack [23]	Outdoor	Multiple	7 (✓)	2	313	2018	Person
MSMT17 [24]	Mixed	12	15 (✓)	15	4101	2018	Person
CityFlowV1 [25]	Outdoor	5	40 (✓)	10	666	2019	Vehicle
MOT20 [26]	Outdoor	8	1	25	—	2020	Person, Vehicle
CityFlowV2 [25]	Outdoor	6	46 (✓)	10	880	2021	Vehicle
MMPTRACK [27]	Indoor	5	23 (✓)	15	—	2023	Person
MEVID [28]	Mixed	17	33 (✓)	—	158	2023	Person

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Challenges:

- MOT [22], [26]
 - AICity [29]
 - VOT(S) [30], [31]

Literature Review

Milestones - Datasets and Challenges



Figure: DukeMTMC [2, Fig. 2]

Literature Review

Tracking Paradigms

- **Tracking-by-Detection**

Literature Review

Tracking Paradigms

- **Tracking-by-Detection**
- Tracking-by-Regression

Literature Review

Tracking Paradigms

- **Tracking-by-Detection**
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- Tracking-by-Segmentation

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Tracking Paradigms

- **Tracking-by-Detection**
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Tracking Paradigms

- **Tracking-by-Detection**
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- Tracking-by-Attention
- **Single-Shot Approaches**

Literature Review

Tracking Paradigms

- **Tracking-by-Detection**
 - Sort [32]
 - DeepSORT [33]
- Tracking-by-Regression
- Tracking-by-Segmentation
- Tracking-by-Attention
- **Single-Shot Approaches**

Literature Review

Tracking Paradigms

- **Tracking-by-Detection**
 - Sort [32]
 - DeepSORT [33]
- Tracking-by-Regression
- Tracking-by-Segmentation
- Tracking-by-Attention
- **Single-Shot Approaches**
 - Tracktor [34]
 - Single-Shot Multi-Object Tracking (SMOT) [35]
 - Joint Detection and Embedding (JDE) [36]
 - FairMOT [37]

Literature Review

Tracking Paradigms

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- Tracking-by-Regression
- Tracking-by-Segmentation
- Tracking-by-Attention
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 - Tracktor [34]
 - Single-Shot Multi-Object Tracking (SMOT) [35]
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 - FairMOT [37]

Note: Only refers to detection and intra-camera tracking
(inter-camera tracking requires additional step)

Literature Review

Graph-Based

- Data association problem as graph

Literature Review

Graph-Based

- Data association problem as graph
- Nodes represent detections

Literature Review

Graph-Based

- Data association problem as graph
- Nodes represent detections
- Edges represent association costs

Literature Review

Graph-Based

- Data association problem as graph
- Nodes represent detections
- Edges represent association costs
- Recently use of Graph Neural Networks (GNNs) [38]

Literature Review

Edge-Computing

- **Advantages:**

- Process data near source
- Reduce latency and bandwidth
- Improve security and privacy (data not stored)

Literature Review

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Edge-Computing

- **Advantages:**
 - Process data near source
 - Reduce latency and bandwidth
 - Improve security and privacy (data not stored)
- **Drawback:** Limited resources
- **Examples:**
 - Multi-Camera TrackingChain (MCTChain) [39]
 - Multi-Camera Tracking using Edge-Computing and Low-Power Communication [40]

Literature Review

Online and Real-Time

- “People Detection and Tracking Using a Fisheye Camera Network” [41]
 - Simulate checkout-free store
 - Fisheye cameras
 - Enter and exit store by scanning QR code
 - POM for data association
 - About 10 FPS without GPU

Literature Review

Online and Real-Time

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 - Enter and exit store by scanning QR code
 - POM for data association
 - About 10 FPS without GPU
- Fast-Constrained Dominant Set Clustering (FCDSC) [1]
 - Graph-based approach
 - Consider only a sub-graph at each step
 - Solve intra- and inter-camera tracking simultaneously
 - About 18 FPS

Literature Review

State-of-the-Art

- Self-supervised Camera Link Model (SCLM) [42]
 - Graph Auto-Encoder (GAE) [43]
 - Zone generation algorithm
 - State-of-the-art on CityFlow 2019 and 2020

Literature Review

State-of-the-Art

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 - State-of-the-art on CityFlow 2019 and 2020
- Lifted Multicut Meets Geometry Projections (LMGP) [44]
 - Use of POM
 - Bottom center of bounding box projection
 - State-of-the-art on Wildtrack

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 - State-of-the-art on Wildtrack
- EarlyBird [45]
 - Early fusion in bird's eye view
 - Encoder network
 - Projection onto ground plane
 - Second best on Wildtrack

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 - Early fusion in bird's eye view
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 - Projection onto ground plane
 - Second best on Wildtrack
- AOT, DeAOT, DMAOT [46], [47]
 - Transformer architecture
 - Segmentation-based tracking
 - Winner of VOTS2023 challenge

Literature Review

Honorable Mentions

- Harry Potter's Marauder's Map [48]
 - Draws parallels to Marauder's Map from Harry Potter
 - Localizes and tracks people
 - Uses color information and face recognition
 - Real-world nursing home, 15 cameras

Literature Review

Honorable Mentions

- Harry Potter's Marauder's Map [48]
 - Draws parallels to Marauder's Map from Harry Potter
 - Localizes and tracks people
 - Uses color information and face recognition
 - Real-world nursing home, 15 cameras
- MTA Dataset [49]
 - MTMCT dataset
 - Virtual environment (GTA V)
 - Innovative approach
 - No privacy concerns

Discussion

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- Summary
- Gaps and Limitations
- Future Research
- Ethical and Privacy Concerns

5 Conclusion

- High complexity of MTMCT systems

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- Many challenges

- High complexity of MTMCT systems
- Many challenges
- A lot of different approaches

Discussion

Gaps and Limitations

- Existing datasets and challenges focus primarily on intra-camera tracking

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- Existing datasets and challenges focus primarily on intra-camera tracking
- No challenge focuses solely on real-time inter-camera tracking

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- No challenge focuses solely on real-time inter-camera tracking
- Intra-camera tracking frameworks not optimized for inter-camera tracking

Discussion

Gaps and Limitations

- Existing datasets and challenges focus primarily on intra-camera tracking
- No challenge focuses solely on real-time inter-camera tracking
- Intra-camera tracking frameworks not optimized for inter-camera tracking
- Trade-off between accuracy and speed

- Evaluation metric for MTMCT systems
(currently based on single-camera tracking metrics)

Discussion

Future Research

- Evaluation metric for MTMCT systems
(currently based on single-camera tracking metrics)
- Challenge for real-time inter-camera tracking

Discussion

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- Evaluation metric for MTMCT systems
(currently based on single-camera tracking metrics)
- Challenge for real-time inter-camera tracking
- Investigate semi- and unsupervised learning approaches
(reduce amount of labeled data)

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Future Research

- Evaluation metric for MTMCT systems
(currently based on single-camera tracking metrics)
- Challenge for real-time inter-camera tracking
- Investigate semi- and unsupervised learning approaches
(reduce amount of labeled data)
- Processing of heterogeneous data

Discussion

Ethical and Privacy Concerns

- Balance technological progress with ethical and privacy concerns

Discussion

Ethical and Privacy Concerns

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- Synthetical data generation

Discussion

Ethical and Privacy Concerns

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- Synthetical data generation
- YOLO developer stopped working due to ethical concerns [50]

Discussion

Ethical and Privacy Concerns

- Balance technological progress with ethical and privacy concerns
- Synthetical data generation
- YOLO developer stopped working due to ethical concerns [50]
- DukeMTMC has been withdrawn due to privacy concerns [51]

Conclusion

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- General

Conclusion

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- Intra-camera tracking well researched

Conclusion

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- Inter-camera tracking still open research area with many challenges, especially in real-time scenarios

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- Need for robust data association methods across cameras
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- Ethical and privacy concerns need to be considered in the development of MTMCT systems

Conclusion

General

- Intra-camera tracking well researched
- Inter-camera tracking still open research area with many challenges, especially in real-time scenarios
- Need for robust data association methods across cameras
- Edge computing could lead to more comprehensive and versatile systems
- Ethical and privacy concerns need to be considered in the development of MTMCT systems
- MTMCT will, as it already does, play an important role in many applications

The End

Thank you for your attention!

Questions? Comments?

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