443 Final Presentation

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Introduction to Multi-Object Tracking (MOT)

Multi-Object Tracking (MOT) involves identifying specific objects across multiple frames of a video

- Consistent classification across entire video
- Re-ID (re-identification) is performed as objects exit and re-enter the field of view
- We are using a single camera tracking

Dataset

 Our dataset consists of animated videos depicting people walking through a room.

 Videos serve as a baseline(training) for our Multi-Object Tracking task.

 The dataset allows us to explore and evaluate different tracking algorithms and techniques in a controlled environment.



Problem Statement

 Goal to develop a multi-object tracking system for tracking objects in video sequences

Focus on tracking desired objects, specifically people

Deliverable: Achieve a high testing accuracy with our test dataset

Detection Challenges

- Challenges in object detection: obstructions, scale variations, cluttered backgrounds
- Inaccurate detections can impact tracking performance
- Overcoming challenges using involves tweaking algorithms
- Applying pre-processing techniques to improve detection quality



















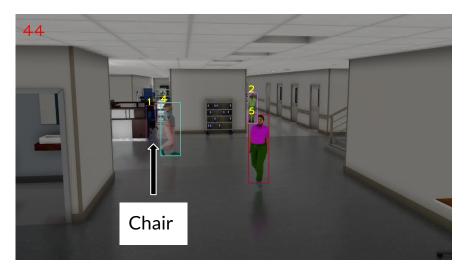


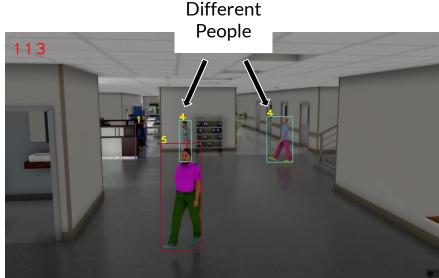


Detection Challenges and Obstacles

Visualized results from running test with original (unchanged) baseline code

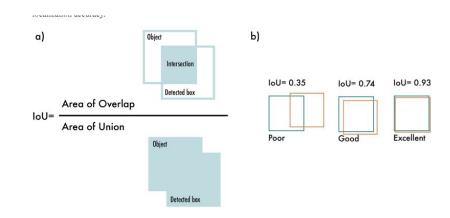
- "Recognizing" objects that are not people
- Classifying two people as the same person





Method Overview

- Two main components:
 - a. single-camera tracking using loU(Intersection over union)
 - b. Post-processing K-means clustering based on appearance
- Added confidence interval filtering to improve accuracy
- Combined approach improves tracking accuracy and reliability



Cosine Differences for Appearance Comparison

- Measure the dissimilarity between appearance features using cosine difference
- Lower cosine difference indicates higher similarity in appearance
- Cosine differences used for clustering and association of objects

Detection 14103 (Video 75)



Detection 14101 (Video 75)



Cosine Difference between the Two: 0.0010015368461608887

Detections Comparison

Detections Comparison

Detection 14108 (Video 75)



Detection 14101 (Video 75)



Object Pair Tracking

- Track object pairs across frames to establish object associations
- Use motion and appearance cues for pairing objects
- Predict object locations based on previous motion patterns
- Object pair tracking ensures continuity in object trajectories

Original



Detection 1





Next Frame









Removing Short Tracklet Merging

- This approach help group tracklets with similar appearances together
- Removing short tracklet merging improves the reliability of object trajectories in multi-object tracking.
- Tracklets are short track segments that capture the movement of objects over a brief period.
- Short tracklets, being brief segments, can introduce noise and inconsistencies to the tracking results.
- Merging short tracklets into longer ones enhances tracking accuracy by creating more complete and continuous trajectories.
- Two common clustering algorithms used for merging tracklets are
 - a. Agglomerative Clustering-recursively merge clusters of sample data by linkage distance
 - b. K-Means Clustering-recursively group data into K groups by distance from centroids

Filtering Low-Confidence Detections

- Remove low-confidence detections to improve tracking accuracy
- Set confidence threshold for detection filtering
- Eliminate detections with low confidence scores
- Focus on high-confidence detections for reliable tracking

```
IDF1 IDP IDR idtp idfp idfn MOTA MOTP Rcll Prcn IDs MT PT ML MultiCam 93.80 94.36 89.14 31039.0 1854.0 3782.0 84.71 10.87 88.33 98.08 658 3 1 1 1 IDF1 IDP IDR idtp idfp idfn MOTA MOTP Rcll Prcn IDs MT PT ML MultiCam 90.81 86.84 89.61 28864.0 4376.0 3348.0 85.51 10.74 93.77 96.32 1586 3 1 1 IDF1 IDP IDR idtp idfp idfn MOTA MOTP Rcll Prcn IDs MT PT ML MultiCam 90.07 79.14 92.48 27525.0 7257.0 2238.0 76.96 10.45 96.73 91.80 3313 3 0 2 IDF1 IDF1 IDP IDR idtp idfp idfn MOTA MOTP Rcll Prcn IDs MT PT ML MultiCam 60.32 51.80 68.65 16870.0 15697.0 7703.0 63.11 9.74 97.99 76.78 1290 4 1 0
```

Camera 74 with confidence thresholds of 0.1, 0.3, 0.6, and 0.8

```
IDF1 IDP IDR idtp idfp idfn MOTA MOTP Rcll Prcn IDs MT PT ML MultiCam 88.08 75.04 92.80 52356.0 17411.0 4061.0 75.31 10.02 99.48 89.86 7303 5 0 0 IDF1 IDP IDR idtp idfp idfn MOTA MOTP Rcll Prcn IDs MT PT ML MultiCam 80.20 66.42 92.48 44219.0 22352.0 3596.0 60.26 9.18 99.99 76.54 4342 5 0 0
```

Observations:

- MOTA (accuracy) highest at 0.3
- MOTP (precision) highest at 0.1
- IDF1 decreases as confidence increases
- Recall increases as confidence increases
- Overall, somewhere between 0.3 and 0.6 is a happy medium

Camera 72 with confidence thresholds of 0.1, 0.3, 0.6, and 0.8

Results and Observations

Shown is Test case video 75 using 0.5 confidence interval.

Some error and mis-detection

Room for improvement



Conclusions

Challenge: implement single-camera MOT with reasonable success and consistency

We could improve through adding a kalman filter or other post processing algorithms

Results depends on how accurate you need to be

MOT is a valuable tool and has many applications

- Security (face, vehicle, object ID in cam footage)
- Social Media/Video Sharing (face tracking for filters)
- Scientific Research (faster classification of observations)