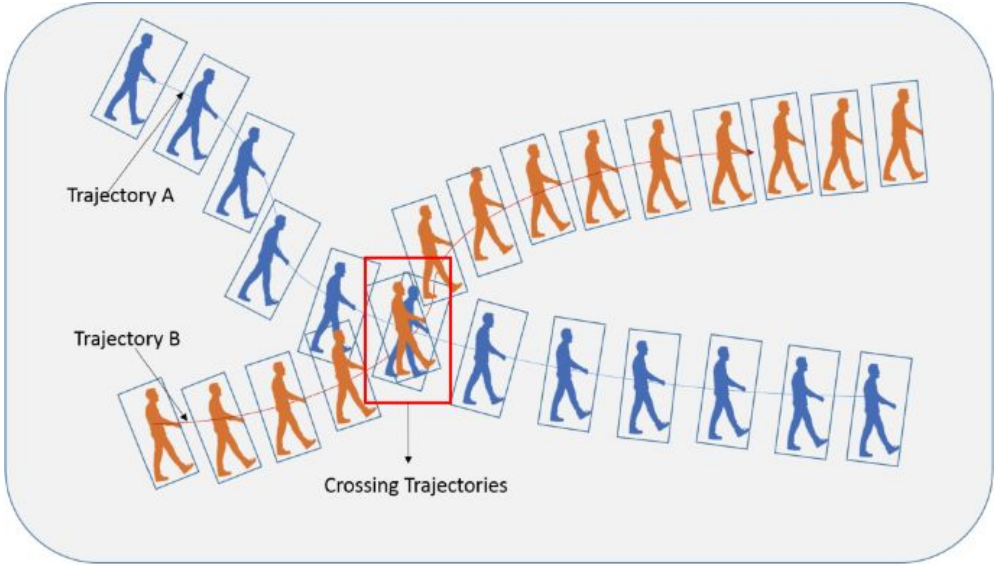
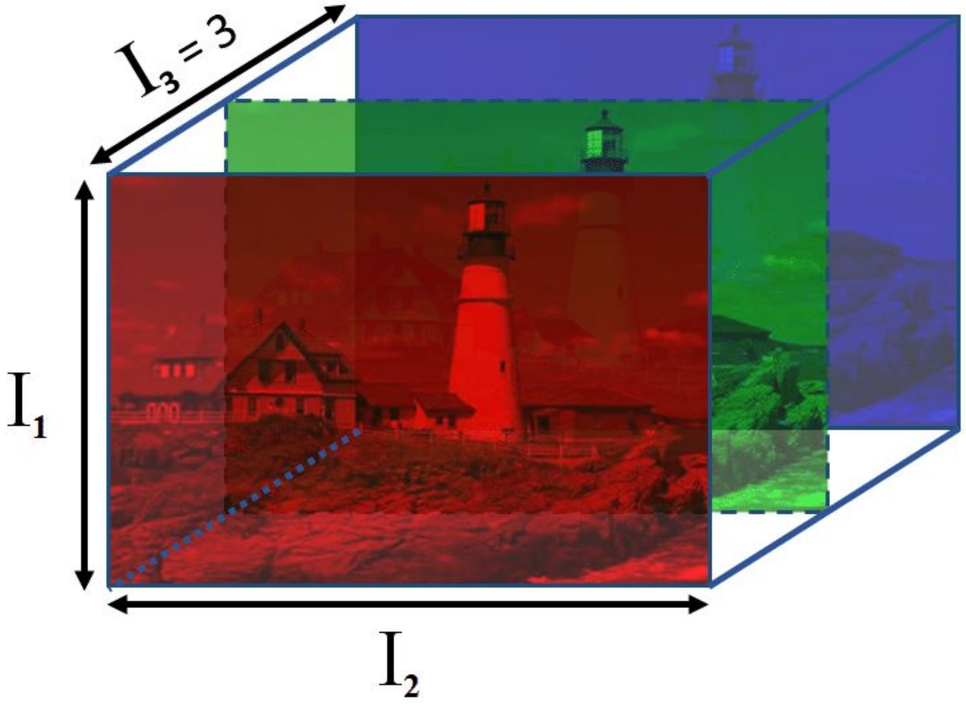
Tracking objects in videos



Luis Cossio
Master in Engineering sciences, mention in Electrical Engineering

Images

- As computational objects, images are represented as 3 matrices of color.
    - Each matrix/channel represent the intensity of a color.
        - Representation Red, Green and Blue (RGB)



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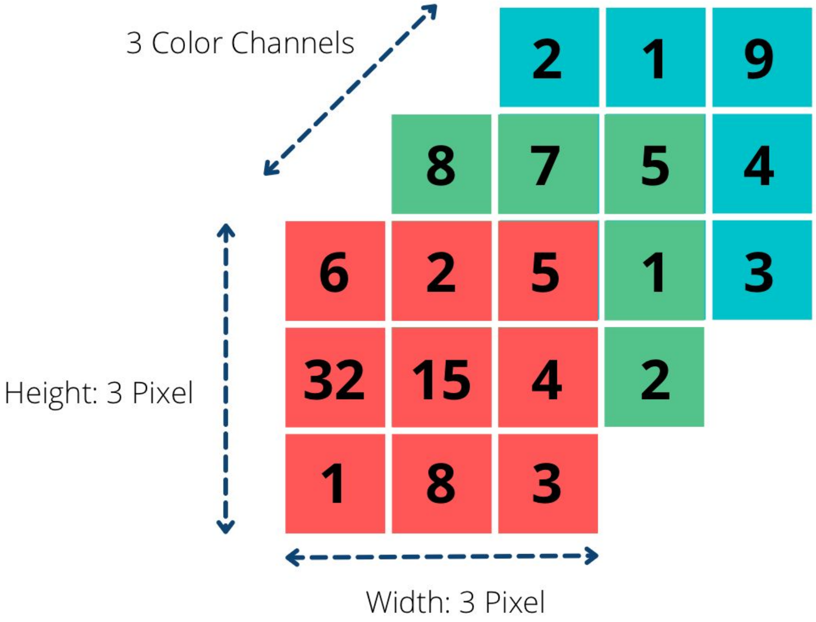
  - Each matrix/channel represent the intensity of a color.
    - Representation Red, Green and Blue (RGB)
  - Individual pixel have values in a given range
    - Unsigned Int scale: [0,255]
    - Float scale: [0.0,1.0]
  - Each value in the image can be accessed by a triplet of indices (i,j,k)



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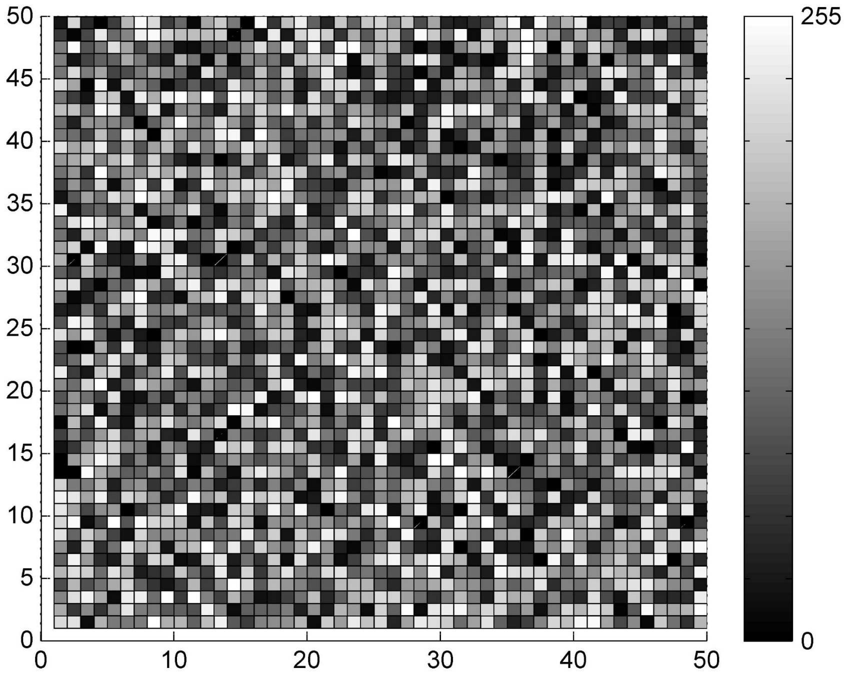
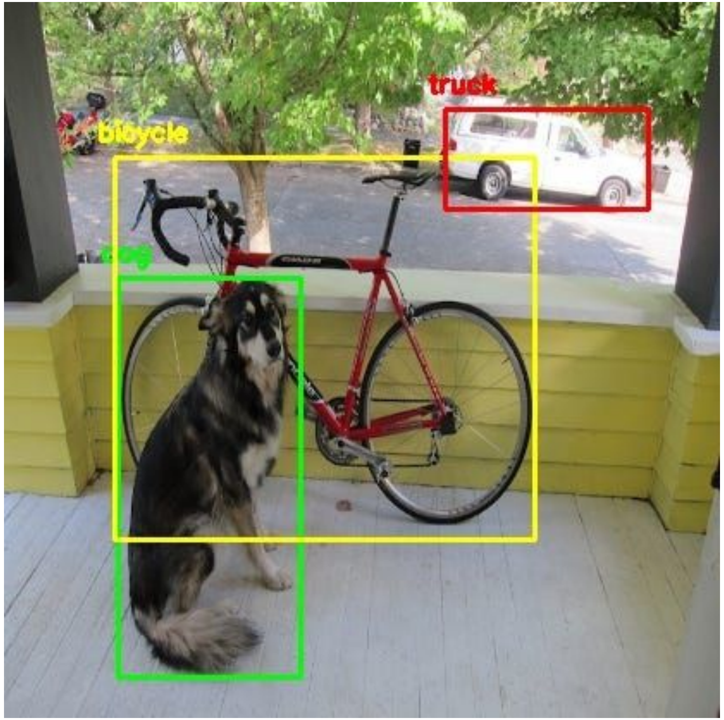
  - Lower values represent darker colors, while higher intensity represent light color



Detection



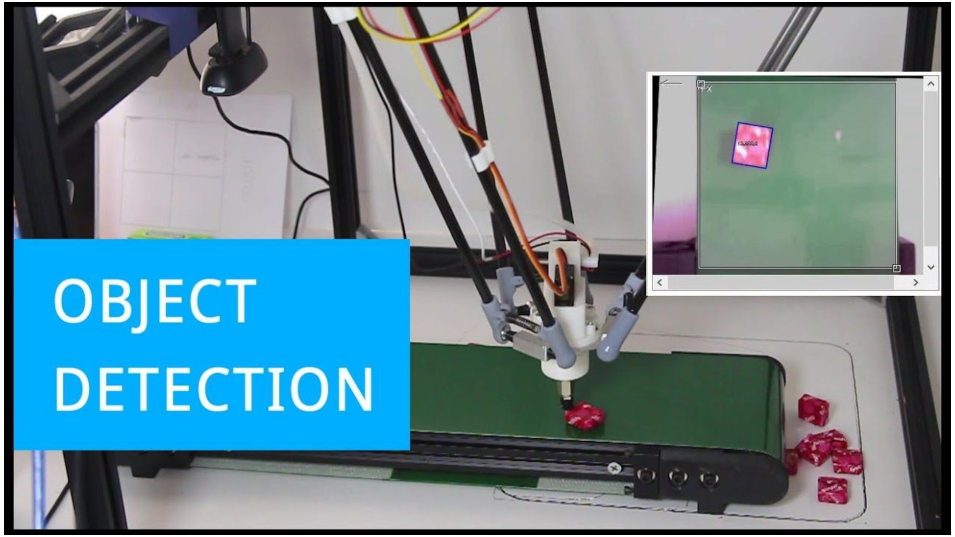
- Detection consist of 3 tasks
  - Separating target objects from background
  - Locating objects
    - Often using a Bounding box
  - Classifying objects in each class

Limitations of detection algorithms

- Surveillance
    - Anomaly Detection

Limitations of detection algorithms

- Simple Robotic Picking
  - Pose estimation
  - Stable setup



Limitations of detection algorithms

- Temperature checking
  - Face Detection
  - Thermal camera

Limitations of detection algorithms

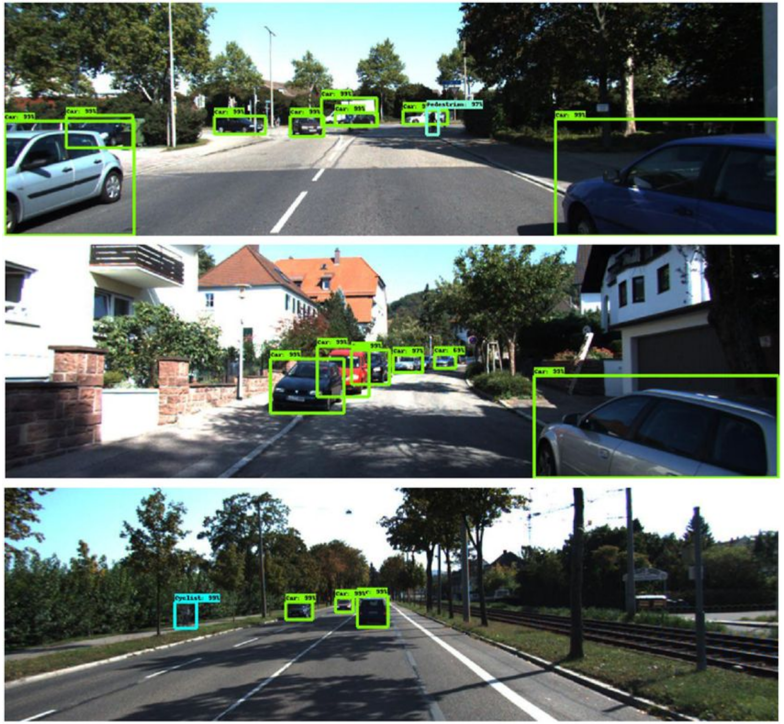
- Crowd-surveillance
  - Detection
  - Tracking
    - Counting

Limitations of detection algorithms

- Sports tracking
  - Detection
  - Tracking
  - 3D triangulation

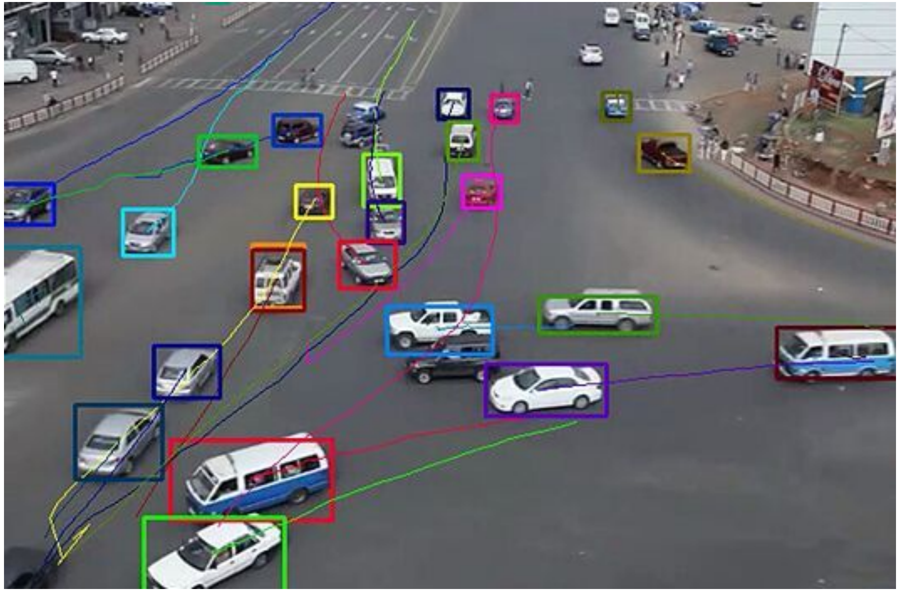
Limitations of detection algorithms

- Self-Driving
  - Detection
  - Tracking
    - Trajectory prediction
  - 3D pose estimation



Tracking Task

- Perform object detection and identification of targets
- Requires pose and visual matching of multiple objects
    - Multi Object Tracking (MOT)



Tracking Task

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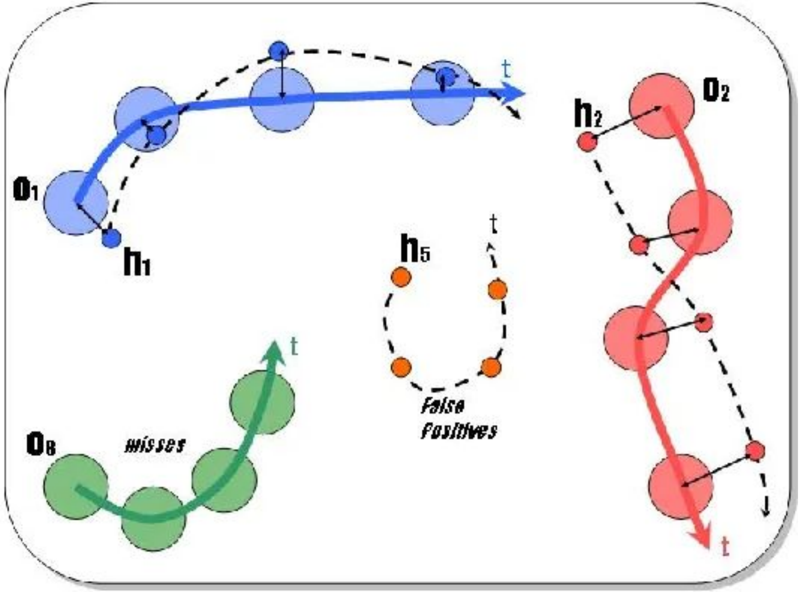
  - Objects don't change their appearance instantaneously
  - The position of objects changes slowly and predictable

Tracking Task

- Very simple task
  - Objects don't change their appearance instantaneously
  - The position of objects changes slowly and predictable
- In practice is hard to automate
  - several types of error can occur

Tracking metrics

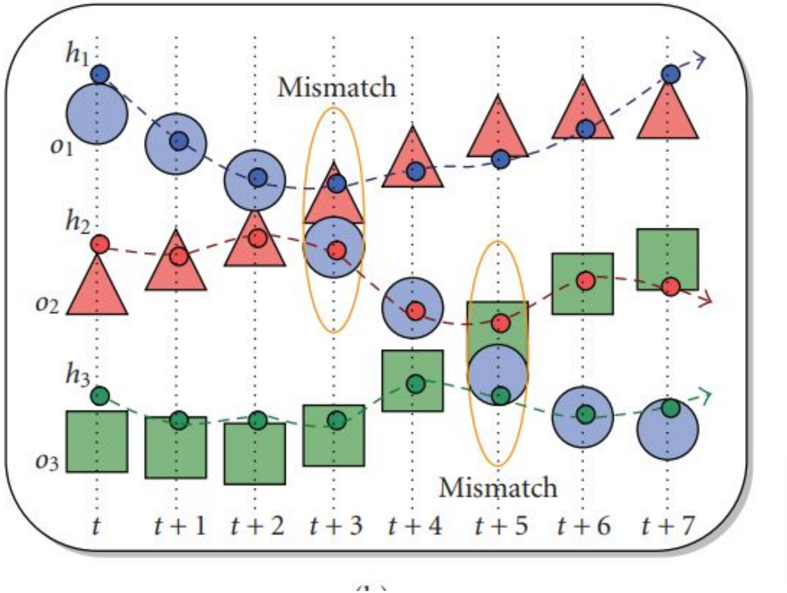
- Positional Metrics
  - Distance L2



Evaluating Multiple Object Tracking Performance: The CLEAR MOT Metrics. 2007

Tracking metrics

- Positional Metrics
  - Distance L2
- Identity Metrics
  - True Positives TP



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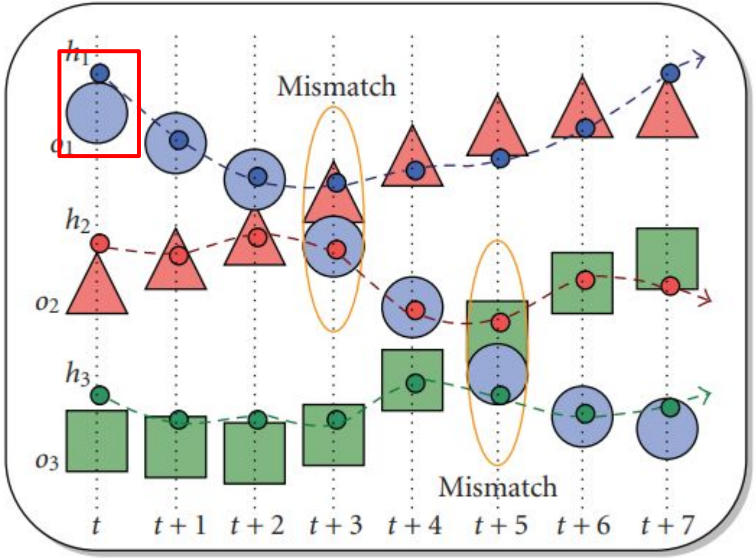

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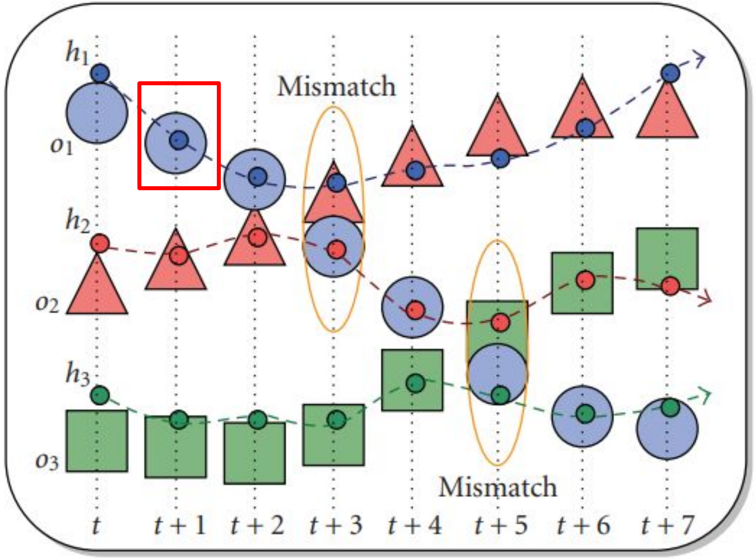

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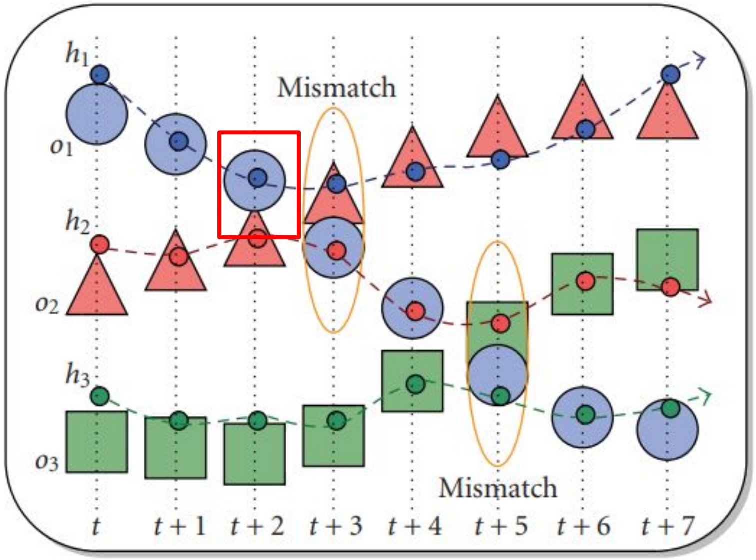
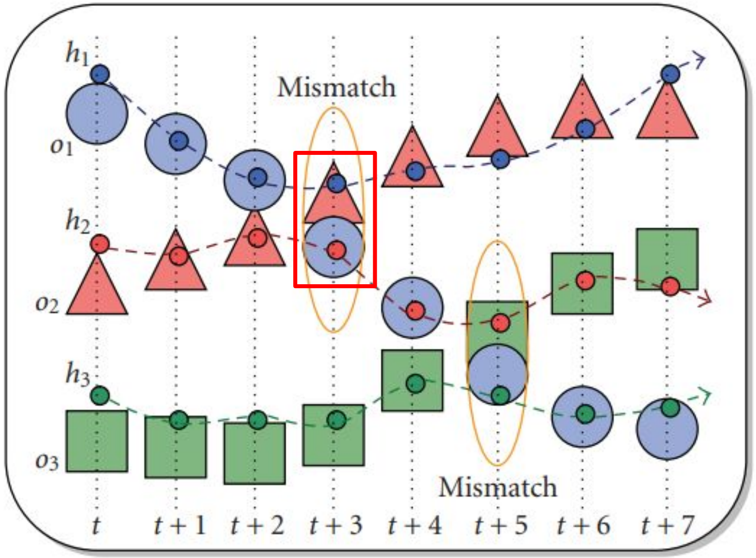


Evaluating Multiple Object Tracking Performance: The CLEAR MOT Metrics. 2007

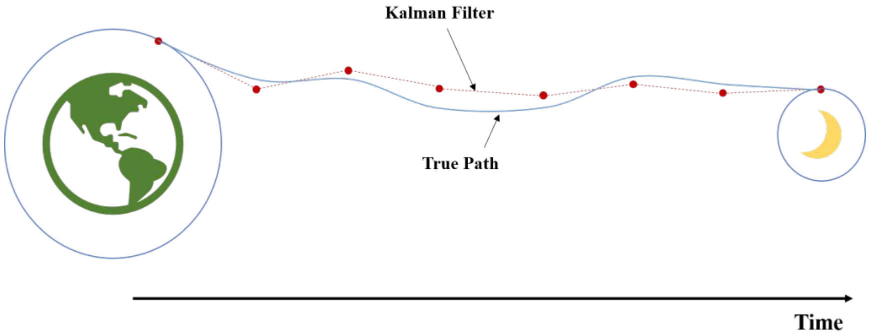
Tracking metrics

- Positional Metrics
  - IoU
  - Distance L2
  - Multi object tracking precision (MOTP)
- Identity Metrics
  - True Positives TP
  - Mismatched



Evaluating Multiple Object Tracking Performance: The CLEAR MOT Metrics. 2007

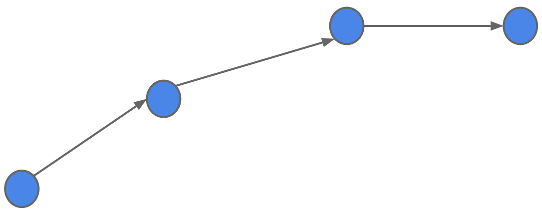
Kalman Tracking



- Kalman Filtering
  - Control algorithm to estimate position of an object
  - One their first uses was the development of a guiding mechanism for the apollo mission.
  - Estimate the position and overall direction of an object using sparse observations.

Kalman Tracking

Real Object



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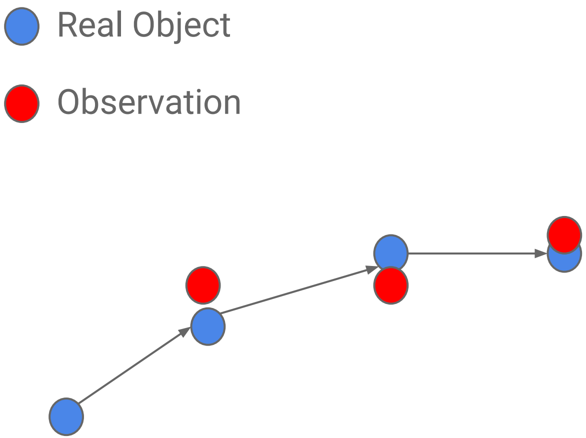

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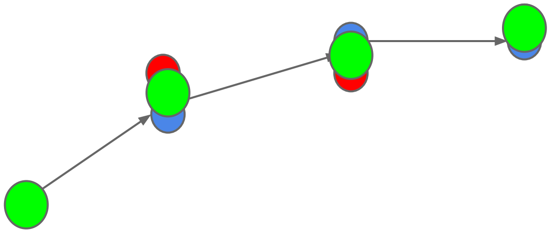
Kalman Tracking

Real Object

Kalman Estimation

Observation



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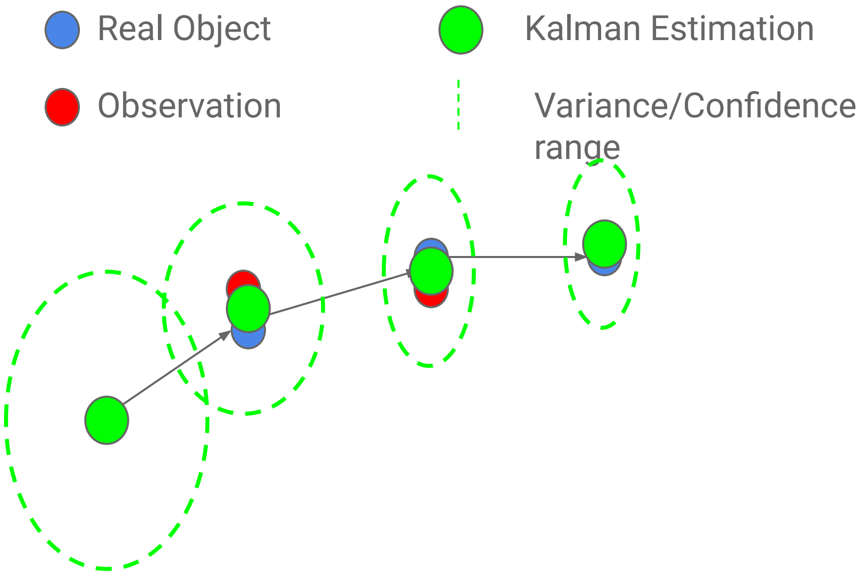

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    - We model the uncertainty of the measurements and the model with a range of confidence/variance.

Kalman Tracking

1. $\hat{X}_{k|k-1} = A\hat{X}_{k-1|k-1} + Bu_k$
2. $P_{k|k-1} = AP_{k-1|k-1}A^T + Q$
3. $J_k = P_{k|k-1}C^T \left(CP_{k|k-1}C^T + R\right)^{-1}$
4. $\hat{X}_{k|k} = \hat{X}_{k|k-1} + J_k \left(Y_k - C\hat{X}_{k|k-1}\right)$
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Kalman Tracking

Previous position in k-1

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3. $J_k = P_{k|k-1}C^T \left(CP_{k|k-1}C^T + R\right)^{-1}$
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Kalman Tracking

Dynamic of the system

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Kalman Tracking

Prior/ expected next step

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Kalman Tracking

Prior variance/uncertainty (NxN)

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Kalman Tracking

Error between expected position / prior and the Observation

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Kalman Tracking

Posterior/predicted position

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Posterior variance

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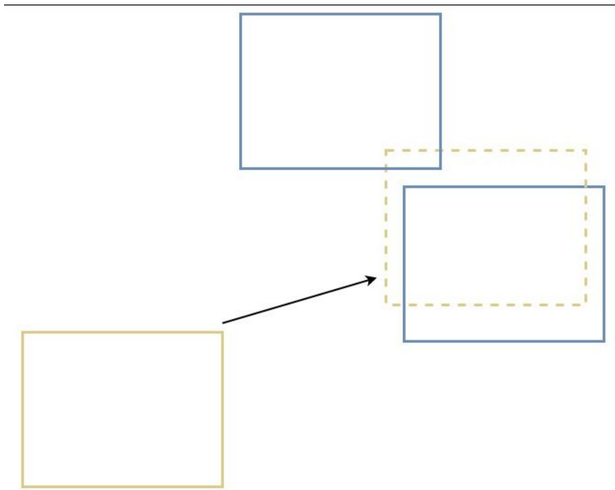
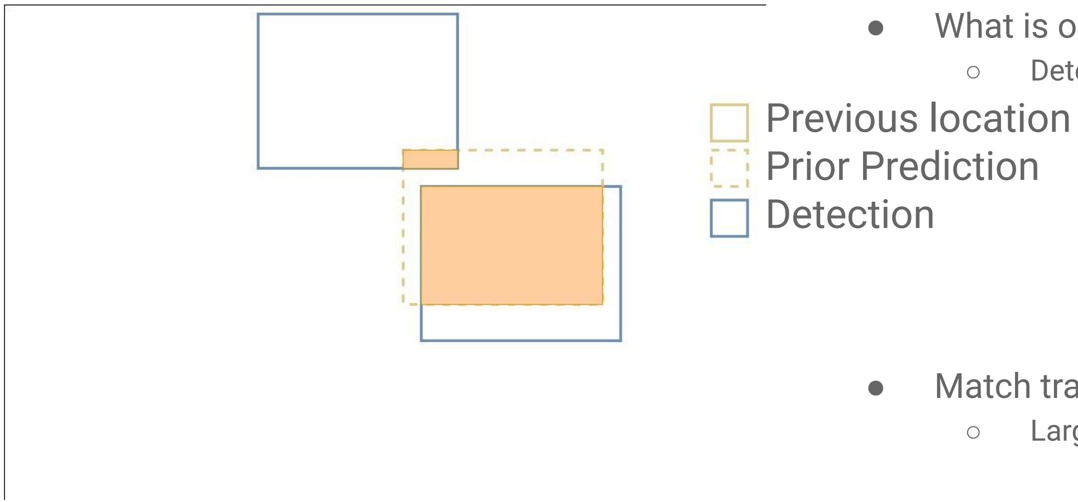
Detection + Kalman Filtering

- What are poses in video tracking?
  - Detections and speeds
    x1,y1,x2,y2,x'1,y'1,x'2,y'2
- What is our input
  - Detections



Previous location
Prior Prediction
Detection

Detection + Kalman Filtering



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- Match track with detection
  - Larger IoU

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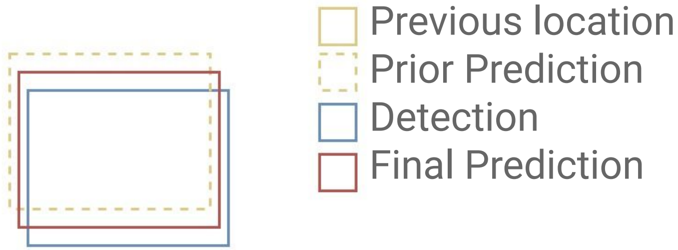

- Match track with detection
  - Larger IoU
- Final Prediction