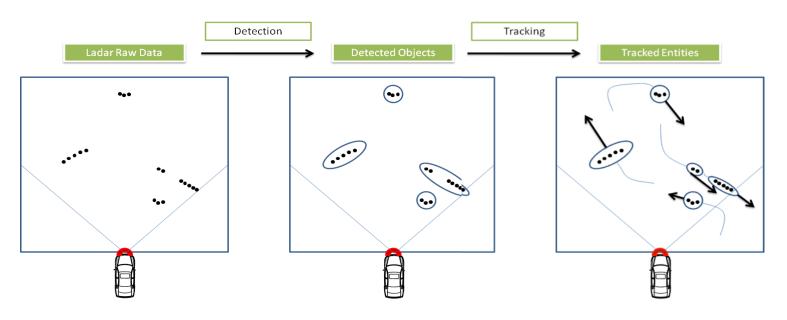
W4. Perception & Situation Awareness & Decision making

- Robot Perception for Dynamic environments: Outline & DP-Grids concept
- Dynamic Probabilistic Grids Bayesian Occupancy Filter concept
- Dynamic Probabilistic Grids Implementation approaches
- Object level Perception functions (SLAM + DATMO)
- Detection and Tracking of Mobile Objects Problem & Approaches
- Detection and Tracking of Mobile Objects Model & Grid based approaches
- Embedded Bayesian Perception & Short-term collision risk (DP-Grid level)
- Situation Awareness Problem statement & Motion / Prediction Models
- Situation Awareness Collision Risk Assessment & Decision (Object level)

DATMO: Intuitive definition (reminder)



Detect objects (e.g. clustering of Lidar data) &

Track over time the moving entities (using previous detections)

Tracking moving objects – What is it about?

Question 1: What is moving objects tracking?

Intuitive definition: Estimates how objects move in the observed dynamic scene

- Question 2: Why to track moving objects?
 - Decision for driving assistance (e.g. trajectories predictions, risk assessment, avoidance strategies...)
 - Confirm the existence of the moving objects in the scene & Characterize their motion parameters (to update the objects models)
 - Compute over time the dynamic data of the scene

Tracking moving objects – *Outline*

Tracking = Estimating over time the **states of multiple moving objects**, by using sets of observations (detection is done)

Data association

- Single-Scan Global Nearest Neighbor (GNN)
 Joint Probability Data Association (JPDA) [Fortman 83]
- N-Scan Multiple Hypotheses Tracking (MHT) [Reid 78]

Filtering

- Single-model Kalman filter (KF, EKF, UKF)
 Particle Filter (PF)
- Multiple-models Interacting Multiple Models (IMM)

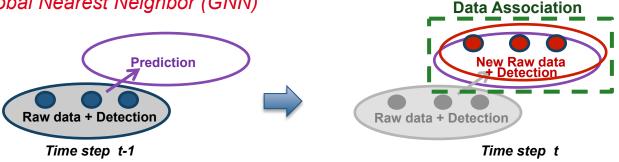
Object representation

- Point-based JPDA + PF (Tracking people) [Schulz et al 01]

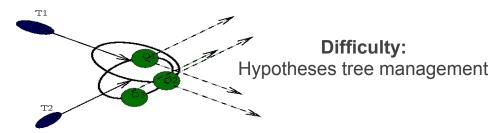
 MHT + IMM (General Objects & Traffic) [Wang 04]
- Model vs Model-free

Data association = Correspondence between the **observation** & the **predicted position** of a given object

• Single-Scan - Global Nearest Neighbor (GNN)



N-Scan - Multiple Hypotheses Tracking (MHT)



Some well-known problems with data association methods

→ Ambiguity & Complexity (one object & several detections)



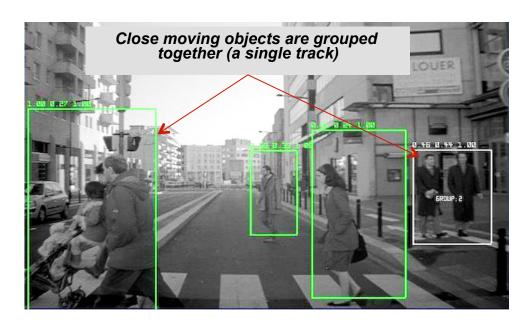
Some well-known problems with data association methods

→ Ambiguity & Complexity (New object appearing close to an other tracked object)



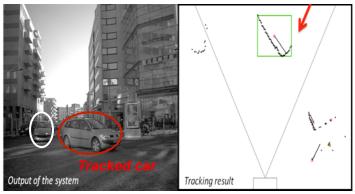
Some well-known problems with data association methods

→ Ambiguity & Complexity (Close objects moving together)

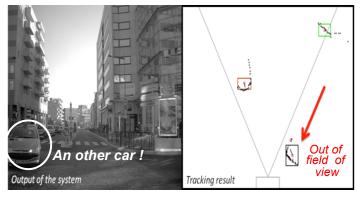


Some well-known problems with data association methods

→ Ambiguity & Complexity (A tracked object disappeared)



Detection & Tracking at time t-1

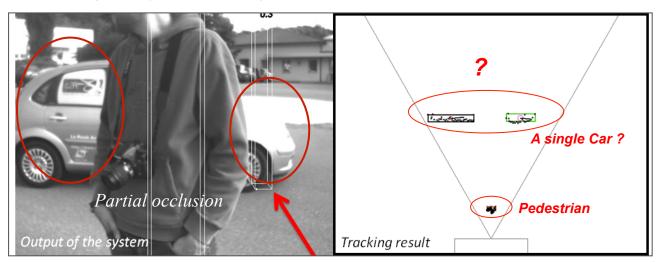


Detection & Tracking at time t ⇒ too big change between two

- - consecutive frames
- ⇒ the previously tracked car disappeared

Some well-known problems with data association methods

→ Temporary Partial Occlusion (A tracked object is split in two parts because of temporary occlusion)



Tracking – Filtering

• Filtering: Tracking a single object when its observations are known over time

Bayesian formulation: Estimating the belief over a state S_t

based on observations $\mathbf{Z}_{1...t}$

$$\rightarrow$$
 bel_t = $P(S_t | Z_{1...t})$?

with:

- State (S_t) = Position (X_t) + Velocity (V_t)
- Markovian Hypothesis: State at time t only depends on state at time t-1

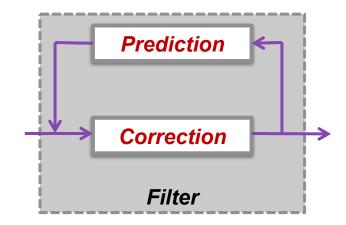
 Z_2

Recursive estimation

$$bel_t = \eta p(Z_t|S_t) \int p(S_t|S_{t-1})bel_{t-1} dS_{t-1}$$
Likelihood model Evolution model

Tracking – The filtering loop

- Prediction (using evolution model)
 - Velocity model: P(V_t | V_{t-1})
 - Motion model: $P(X_t | X_{t-1}, V_t)$
 - e.g. constant velocity model between time t-1 and time t
 - \checkmark $\bigvee_{t=1}^{t}$
 - $V X_t = X_{t-1} + V_{X,t}$. dt
 - $\vee Y_{t} = Y_{t-1} + V_{Y,t}$. dt
- Correction (using observation model)
 - Observation model : P(Z_t | X_t)



Exercise:

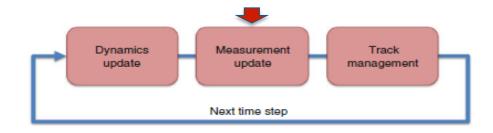
Expressing the Filtering loop using the Kalman Filter

```
    X<sub>t</sub> = F<sub>t</sub> X<sub>t-1</sub> + B<sub>t</sub> U<sub>t</sub> + W<sub>t</sub> → Prediction step with: F<sub>t</sub> = state transition (evolution model)
    U<sub>t</sub> = control
    W<sub>t</sub> = processed noise
```

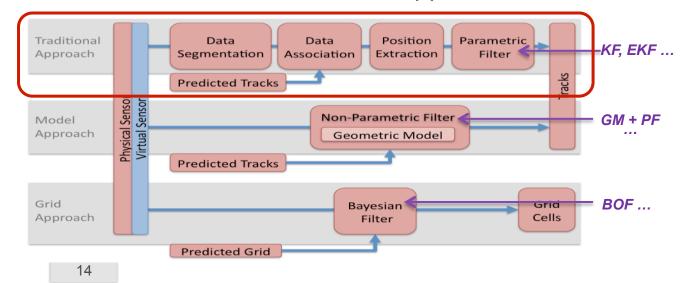
- Z_t = G_t X_t + V_t → Correction step
 with: G_t = observation model
 V_t = observation noise
- e.g. for constant velocity: $F_t = \begin{bmatrix} 1 & 0 & dt & 0 \\ 0 & 1 & 0 & dt \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$

DATMO – Outline & Main approaches

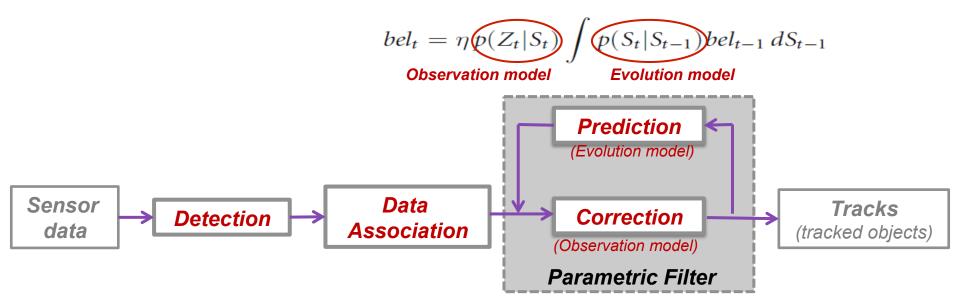
Typical DATMO Pipeline



Three main classes of DATMO Approaches



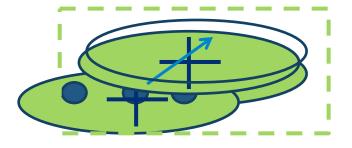
Traditional DATMO approaches – *Processing flow*



Traditional DATMO approaches – *Illustration*

- Raw data (time t-1)
- Detection
- Estimation /correction
- Prediction
- New data (time t)
- Detection
- Data Association
- Correction





Traditional DATMO Approaches – Conclusion

- Several possible implementations
- Works quite well on some identified classes of problems
 ... but well-known problems with Laser-based Tracking (point-clouds tracking)
 & Data Association still hold => Objects splitting, Appearing & disappearing targets, Errors in data associations ...
- Next session will show how to improve these approaches using "Models" or "Grid Approaches"