

## 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)

# DP-Grids – *How to compute $P(OV | Z C)$ in practice?*

*Theoretical solving (see previous session)*

$$P(OV | ZC) = \lambda \sum_{A O^{-1} V^{-1}} P(C A O O^{-1} V V^{-1} Z)$$

Sum over the possible antecedents A and their states ( $O^{-1} V^{-1}$ )

With:  $P(C A O O^{-1} V V^{-1} Z) = P(A) P(O^{-1} V^{-1} | A) P(O V | O^{-1} V^{-1})$   
 $P(C | A V) P(Z | O C)$

*Computing this expression is difficult in practice*

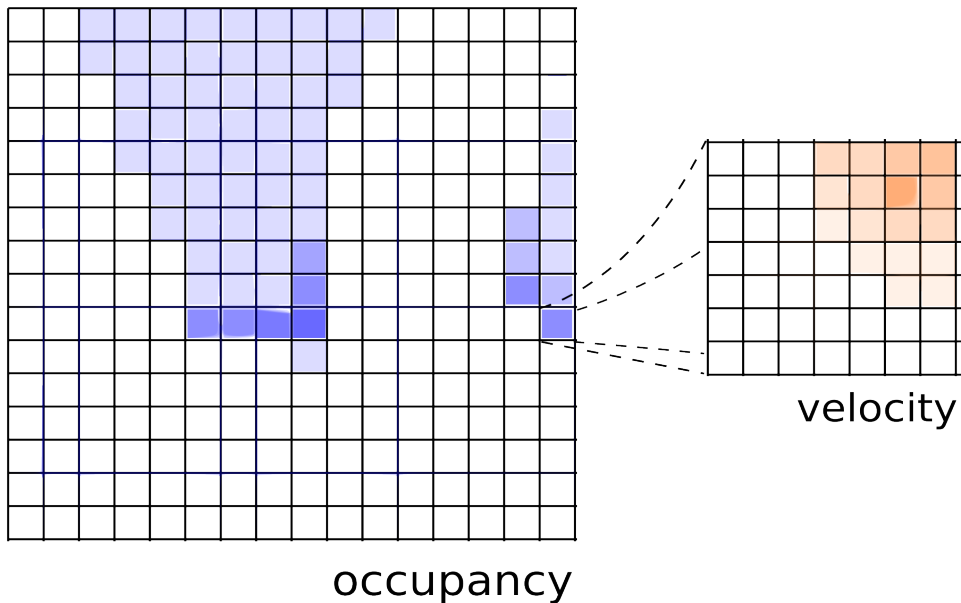
*=> Huge range of possible antecedents*

*=> Strongly depends on grid size & velocity range*

# DP-Grids – *How to compute $P(OV | Z C)$ in practice?*

## *Initial approach: The classic BOF*

- Regular grid
- Transition histograms for every cell (for representing velocities)



# DP-Grids – How to compute $P(OV | Z C)$ in practice?

## Initial approach: The classic BOF

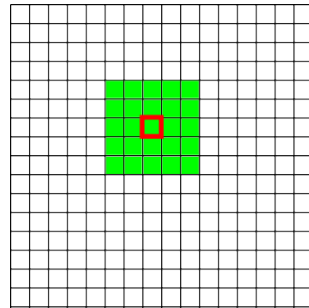
$$P(OV | ZC) = \lambda \sum_{A O^{-1} V^{-1}} P(C A O O^{-1} V V^{-1} Z)$$

Sum over the possible antecedents  $A$  and their states  $(O^{-1} V^{-1})$

**Practical computation:**

→ Sum over the **neighborhood**, with a **single possible velocity per antecedent  $A$**  of equation:

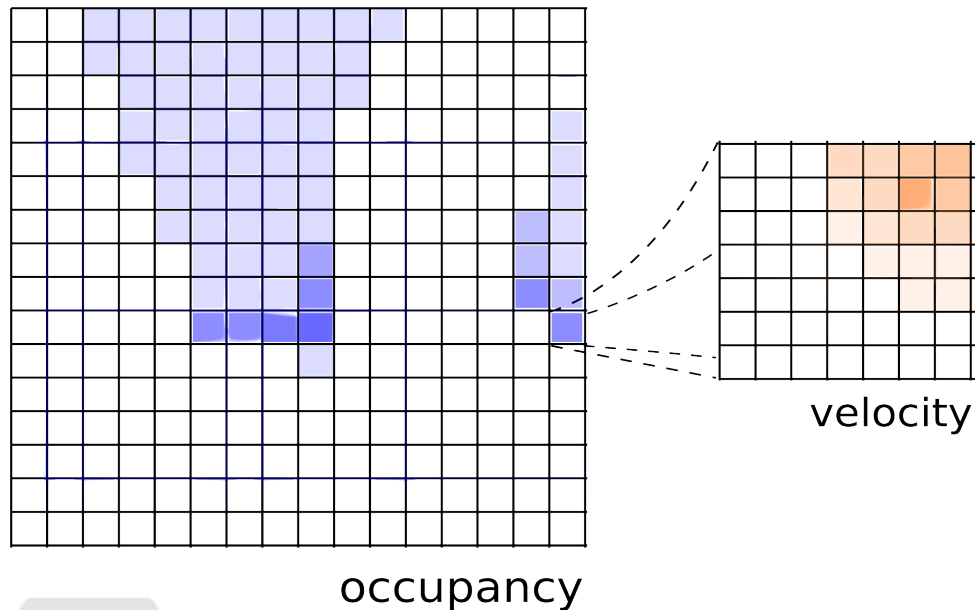
$$P(C A O O^{-1} V V^{-1} Z) = P(A) P(O^{-1} V^{-1} | A) P(O V | O^{-1} V^{-1}) \\ P(C | A V) P(Z | O C)$$



# DP-Grids – *How to compute $P(OV \mid Z C)$ in practice?*

## *Initial approach: Drawbacks*

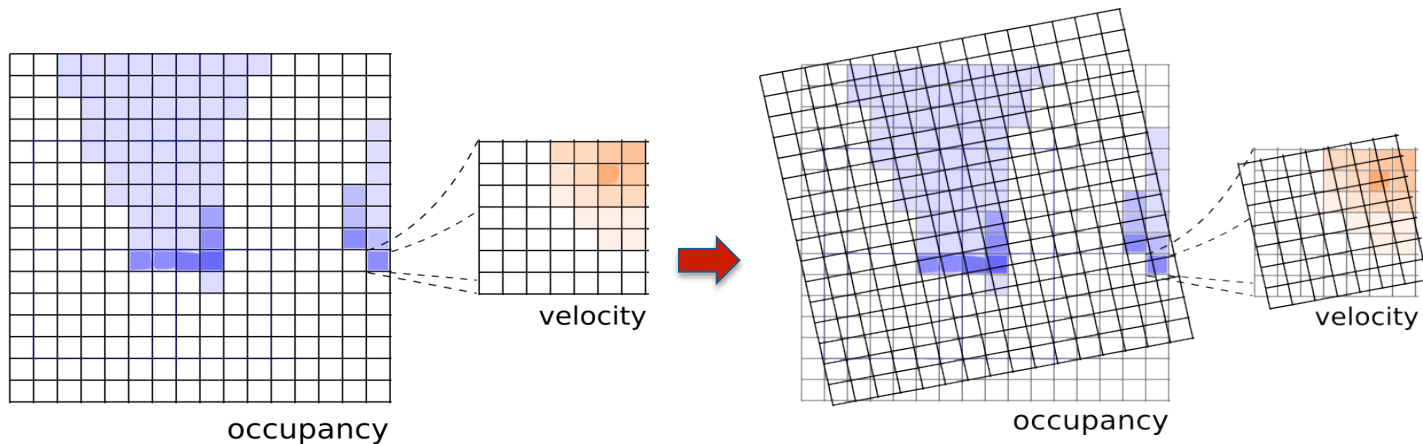
- *Velocity histogram needs to be accurate on both low & high velocities*
  - *Its resolution has to be high, while being **mostly empty***
  - *It requires a **large memory size** (but in practice the accuracy is weak)*



# DP-Grids – *How to compute $P(OV | Z C)$ in practice?*

## *Initial approach: Drawbacks*

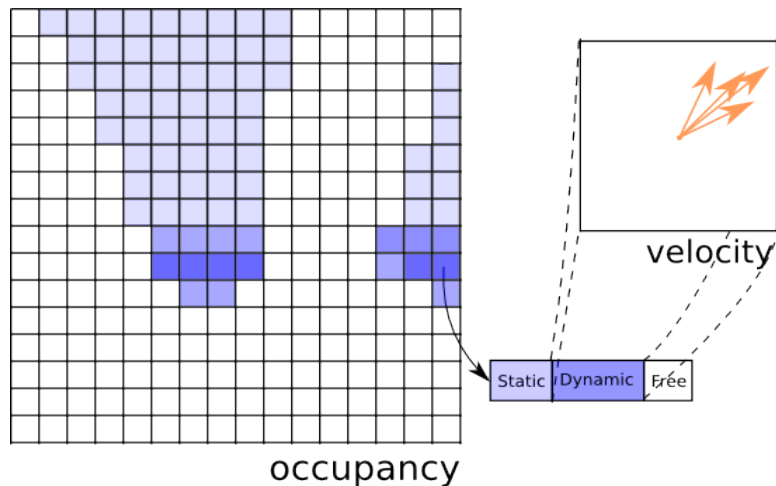
- **Temporal aliasing** → *Due to update / real frequencies synchronization*
- **Spatial aliasing** (moving grid) → *High complexity due to 4-dimension interpolation, approximations required in practice*



# DP-Grids – *How to compute $P(OV | Z C)$ in practice?*

## *Improvement: Hybrid Sampling BOF (HSBOF)*

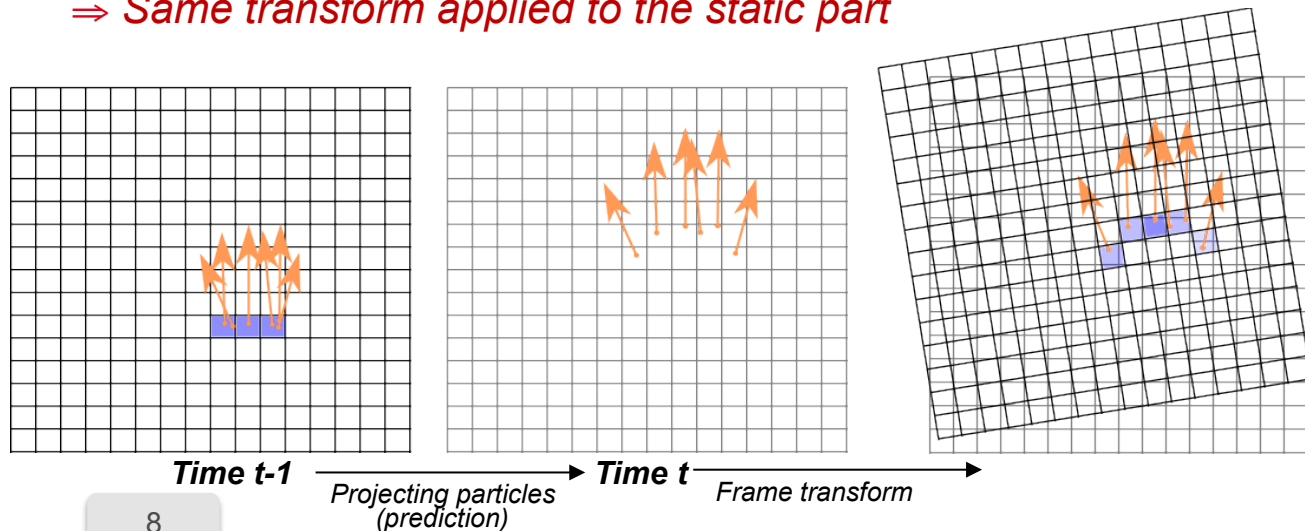
- **Basic idea:** *Modify the representation structure to avoid the previous computational problems*
  - ✓ Making a clear distinction between **Static & Dynamic & Free** components
  - ✓ Modeling velocity using **Particles** (*instead of histogram*)
  - ✓ Making an **adaptive repartition** of those particles in the grid



# DP-Grids – How to compute $P(OV | Z C)$ in practice?

## HSBOF updating process (principle)

- Introducing a Dynamic model for “projecting” particles in the grid ( $S_{t-1} \rightarrow S_t$ )
  - ⇒ Immediate antecedent association
  - ⇒ Simplified velocity prediction to the cells
- Updating Grid Reference Frame
  - ⇒ Translation & Rotation values provided by sensors (Odometry + IMU)
  - ⇒ Same transform applied to the static part



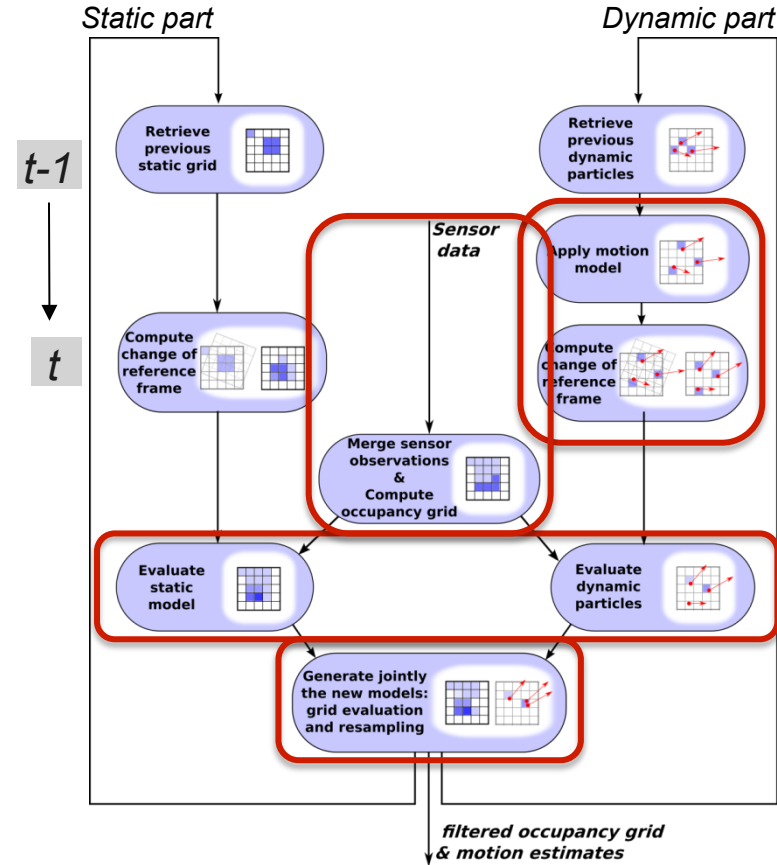


# DP-Grids – How to compute $P(OV | Z C)$ in practice?

## HSBOF updating process (outline)

### Important steps in the updating process

- Dynamic part (particles) is “**projected**” in the grid using motion model (*motion prediction*)
- Both Dynamic & Static parts are expressed in the **new reference frame** (*moving vehicle frame*)
- The two resulting representations are confronted to the **observations** (*estimation step*)
- New representations (static & dynamic)** are jointly evaluated and particles re-sampled



# DP-Grids – How to compute $P(OV | Z C)$ in practice?

## HSBOF filtering calculation

$$P(OV | ZC) = \lambda \sum_{A O^{-1} V^{-1}} P(C A O O^{-1} V V^{-1} Z)$$

Sum over the neighborhood, with a single velocity per antecedent

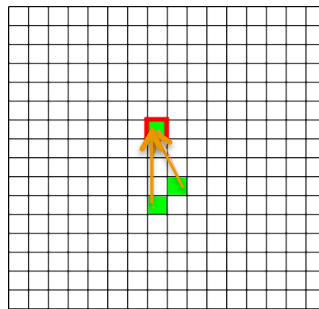
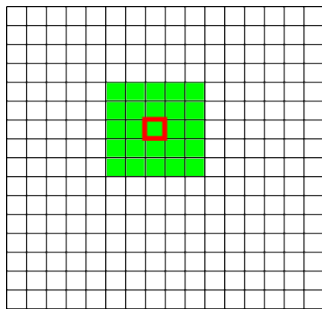
### New computation approach

→ Sum over **the particles projected in the cell** & their **related static parts**

$$P(C A O O^{-1} V V^{-1} Z) = P(A) P(O^{-1} V^{-1} | A) P(O V | O^{-1} V^{-1})$$

$$P(C | A V) P(Z | O C)$$

Previous  
computation approach

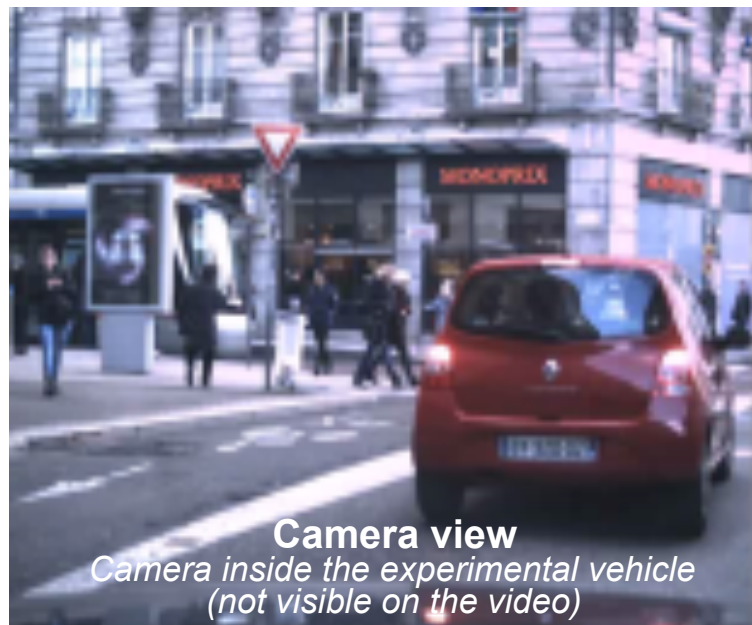


New  
computation approach

# HSBOF: Main features

- Empty & Static components → **Occupancy Grid**
- Dynamic components → **Sets of Particles** (Motion field)
  - ✓ *Smooth integration of the ego-motion (IMU & Odometry)*
  - ✓ *Propagation of sets of particles in the Grid*
  - ✓ *Joint estimation of distributions*
- More efficient (computation & memory) & Better estimation of velocities

# Experimental results in urban environment



**Occupancy Grids**  
*Constructed using Left & Right lasers*



**Motion field**  
*(in red color in the video)*

