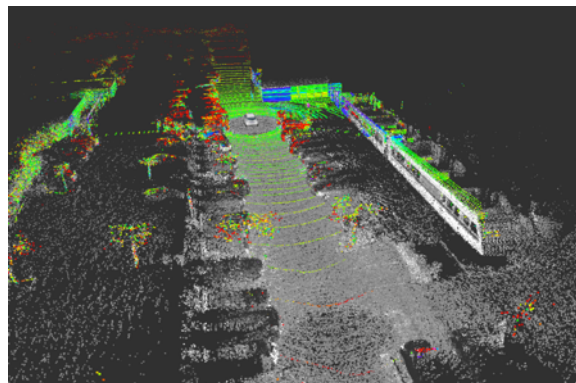


W4. Perception & Situation Awareness & Decision making

- 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)

Dynamic Probabilistic Grids (DP-Grids): *Objective*

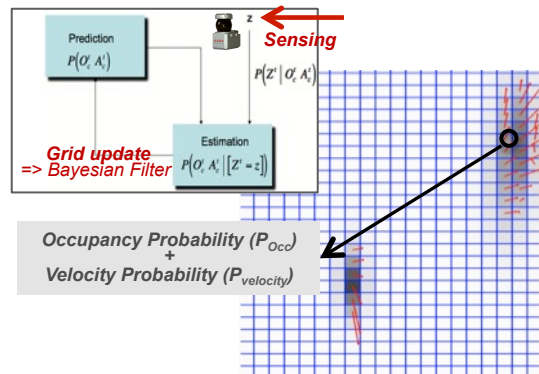
- **Perceive dynamic environment** using various imperfect sensors data (*noise, uncertainty ...*)
- **Interpret data through Spatial Occupancy & Motion** representations
- **Perform real-time analysis** => *usable on embedded devices for Mobile Robots & Intelligent Vehicles*
- **Allows conservative Collision Risk analysis** (*at DP-Grid level*)



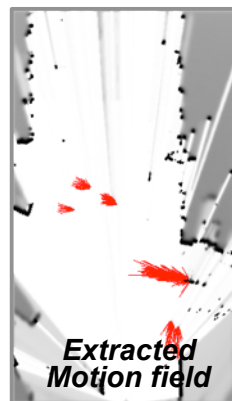
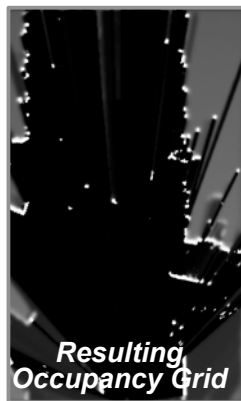
Bayesian Occupancy Filter (BOF): *Outline*

Main features:

- Estimate **Spatial occupancy**
- Analyze **Motion Field** (*using Bayesian filtering*)
- **Without object segmentation** (*i.e. at DP-Grid level*)

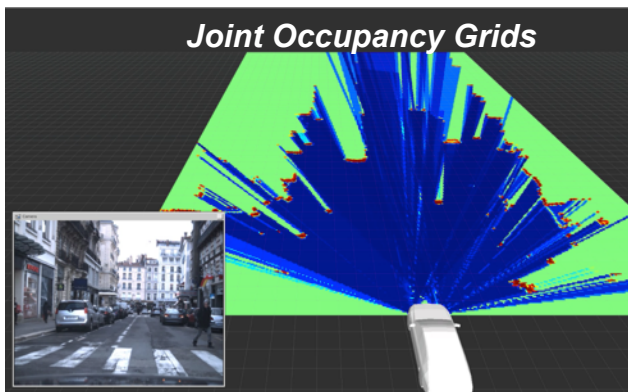
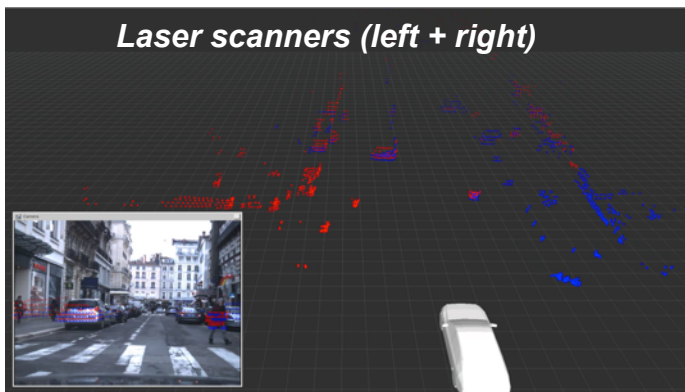


Sensors data fusion
+
Bayesian Filtering



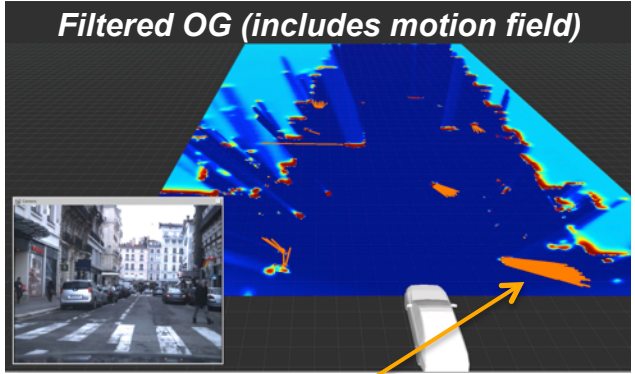
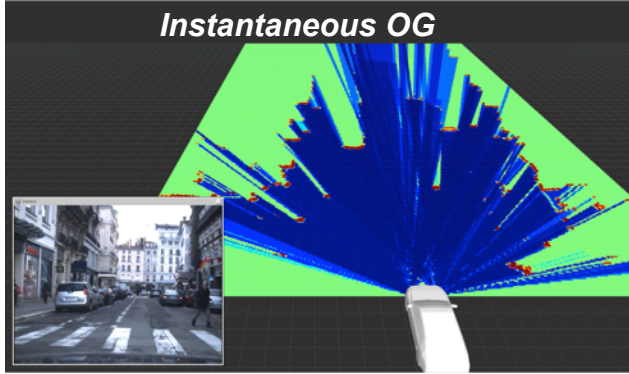
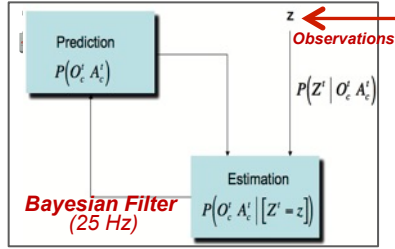
Data fusion: *The joint Occupancy Grid*

- Observations Z_i are given by each sensor i (*Lidars, cameras, etc*)
- For each set of observation Z_i , Occupancy Grids are computed: $P(O | Z_i)$
- Individual grids are merged into a single one: $P(O | Z)$



From instantaneous grids to a *Filtered Occupancy Grid (Bayesian filtering)*

- **Filtering** is achieved through the *prediction/correction loop (Bayesian Filter)*. It allows to take into account grid changes over time
- **Observations** are used to update the environment model
- Update is performed in each cell in parallel (*using BOF equations*)
- **Motion field** is constructed from the resulting filtered data



Motion field is represented in orange color

Bayesian Occupancy Filter – Formalism

- **Features to be assessed** are represented by *Random Variables*
ex : X_1, X_2, X_3, \dots
- **Dependencies between the variable distributions** are made explicit using *Bayesian expressions*
ex : $P(XYZ) = P(X) P(Y | X) P(Z | Y)$
- The **distributions** are updated *according to sensors observations*
- **Interpretation** is achieved *using the obtained distributions*

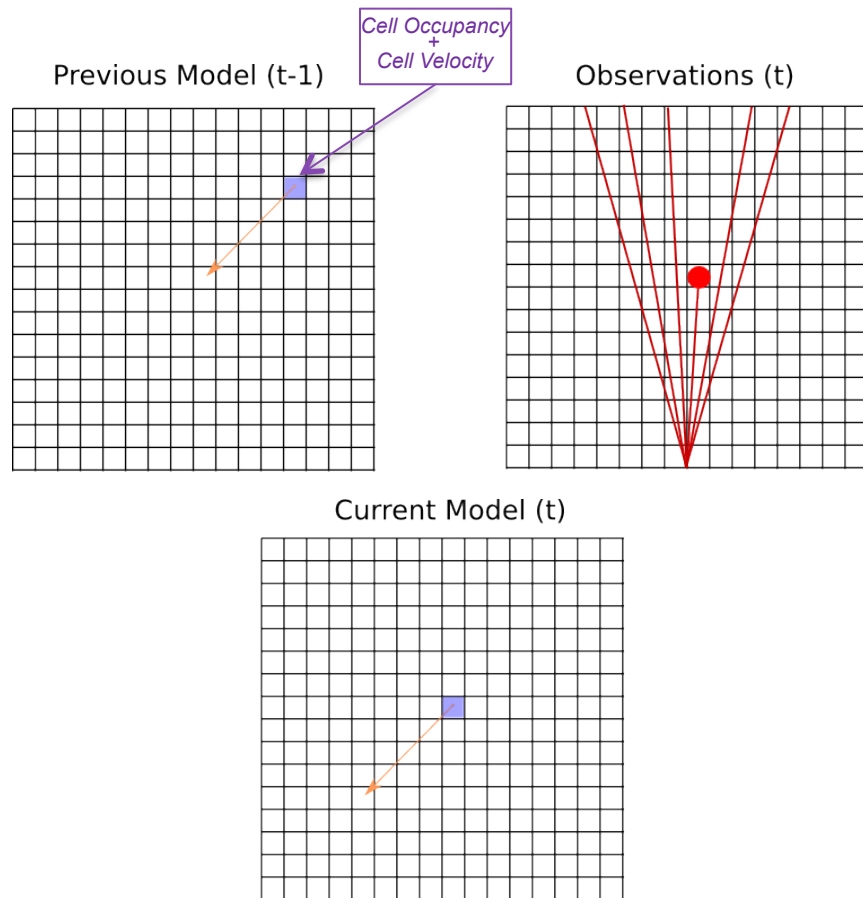
Bayesian Occupancy Filter – Formalism

Variables:

- C : current cell
- A : antecedent cell, i.e. the cell from which the occupancy of the current cell comes from
- O : occupancy of the current cell C
- O^{-1} : previous occupancy in the antecedent cell
- V : current velocity
- V^{-1} : previous velocity in the antecedent
- Z : observations (sensor data)

Objective:

- $P(O \ V \mid Z \ C)$: probability of occupancy & velocity, knowing the cell location & the observations



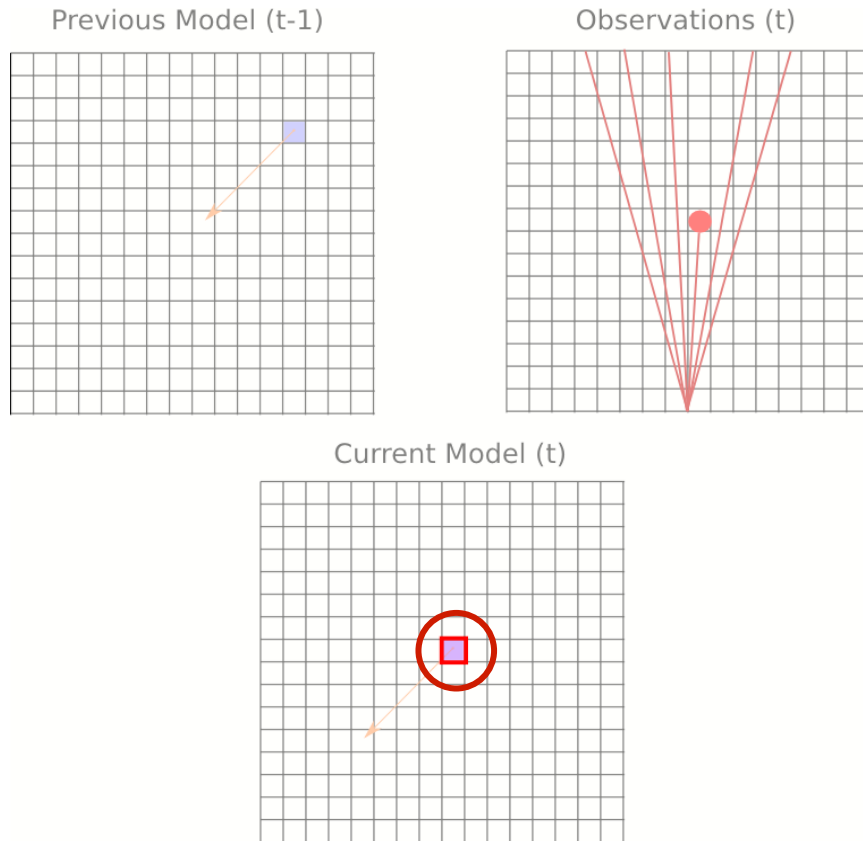
Bayesian Occupancy Filter – Formalism

Variables:

- **C** : current cell (time t)
- A : antecedent cell, i.e. the cell from which the occupancy of the current cell comes from
- O : occupancy of the current cell C
- O^{-1} : previous occupancy in the antecedent cell A
- V : current velocity
- V^{-1} : previous velocity in the antecedent
- Z : observations (sensor data)

Objective:

- $P(O \ V \ | \ Z \ C)$: probability of occupancy & velocity, knowing the cell location & the observations



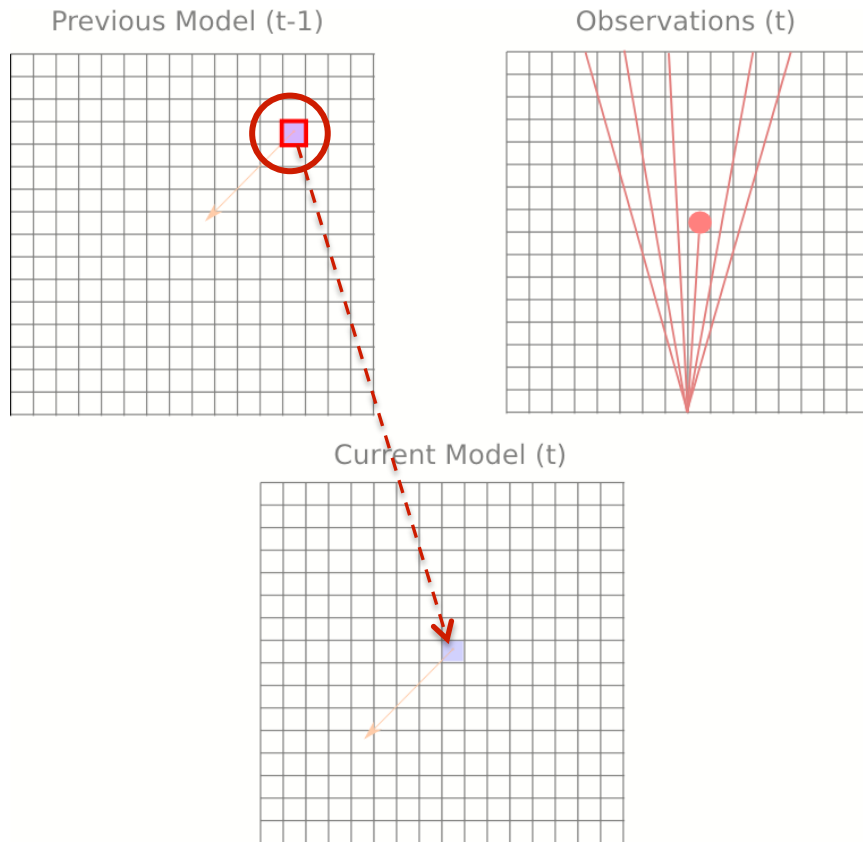
Bayesian Occupancy Filter – Formalism

Variables:

- C : current cell
- A : antecedent cell (time $t-1$), i.e. the cell from which the occupancy of the current cell C (time t) comes from
- O : occupancy of the current cell C
- O^{-1} : previous occupancy in the antecedent cell A
- V : current velocity
- V^{-1} : previous velocity in the antecedent
- Z : observations (sensor data)

Objective:

- $P(O V | Z C)$: probability of occupancy & velocity, knowing the cell location & the observations



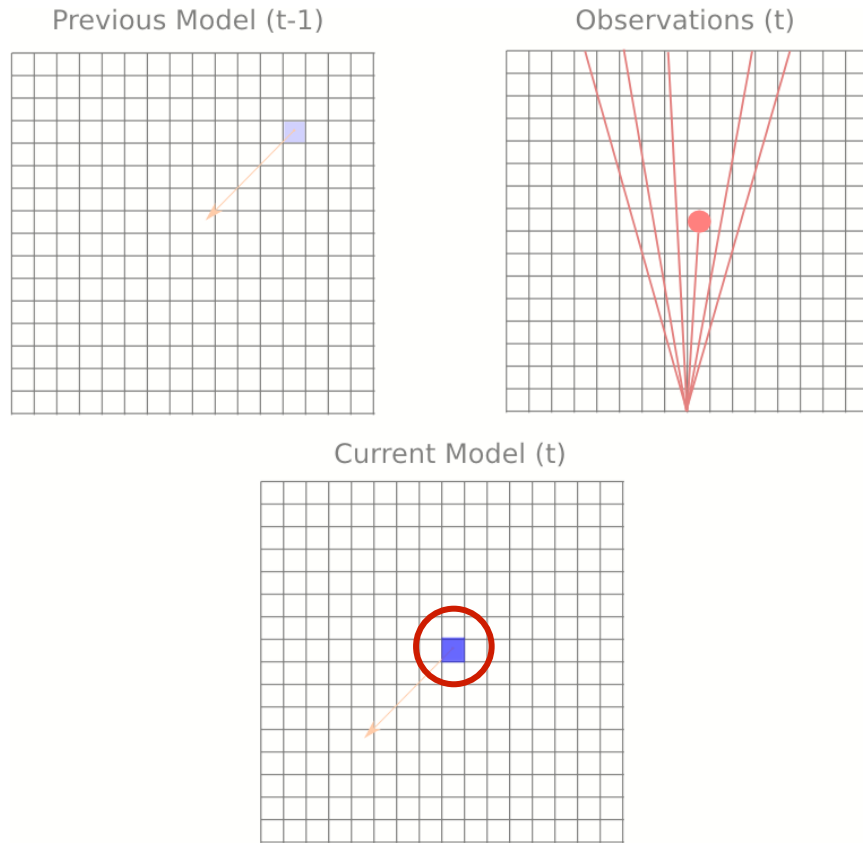
Bayesian Occupancy Filter – Formalism

Variables:

- C : current cell
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- **O : occupancy of the current cell C (time t)**
- O^{-1} : previous occupancy in the antecedent cell A
- V : current velocity
- V^{-1} : previous velocity in the antecedent
- Z : observations (sensor data)

Objective:

- $P(O V | Z C)$: probability of occupancy & velocity, knowing the cell location & the observations



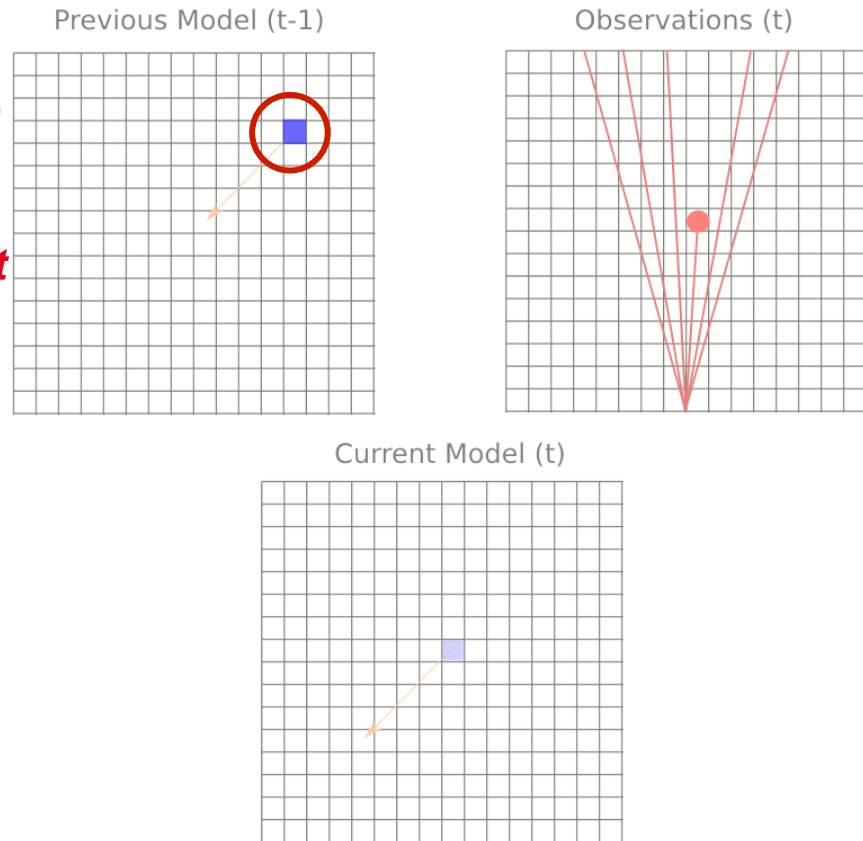
Bayesian Occupancy Filter – Formalism

Variables:

- C : current cell
- A : antecedent cell, i.e. the cell from which the occupancy of the current cell comes from
- O : occupancy of the current cell C
- O^{-1} : previous occupancy in the antecedent cell A (time $t-1$)
- V : current velocity
- V^{-1} : previous velocity in the antecedent
- Z : observations (sensor data)

Objective:

- $P(O V | Z C)$: probability of occupancy & velocity, knowing the cell location & the observations



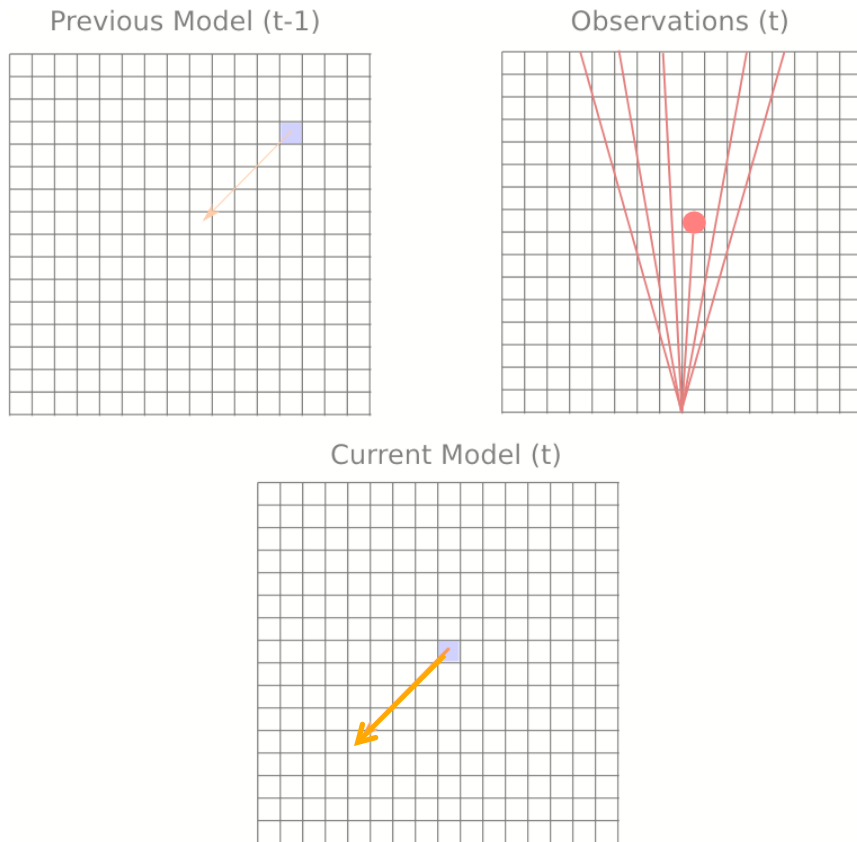
Bayesian Occupancy Filter – Formalism

Variables:

- C : current cell
- A : antecedent cell, i.e. the cell from which the occupancy of the current cell comes from
- O : occupancy of the current cell C
- O^{-1} : previous occupancy in the antecedent cell
- **V : current velocity in cell C (time t)**
- V^{-1} : previous velocity in the antecedent
- Z : observations (sensor data)

Objective:

- $P(O V | Z C)$: probability of occupancy & velocity, knowing the cell location & the observations



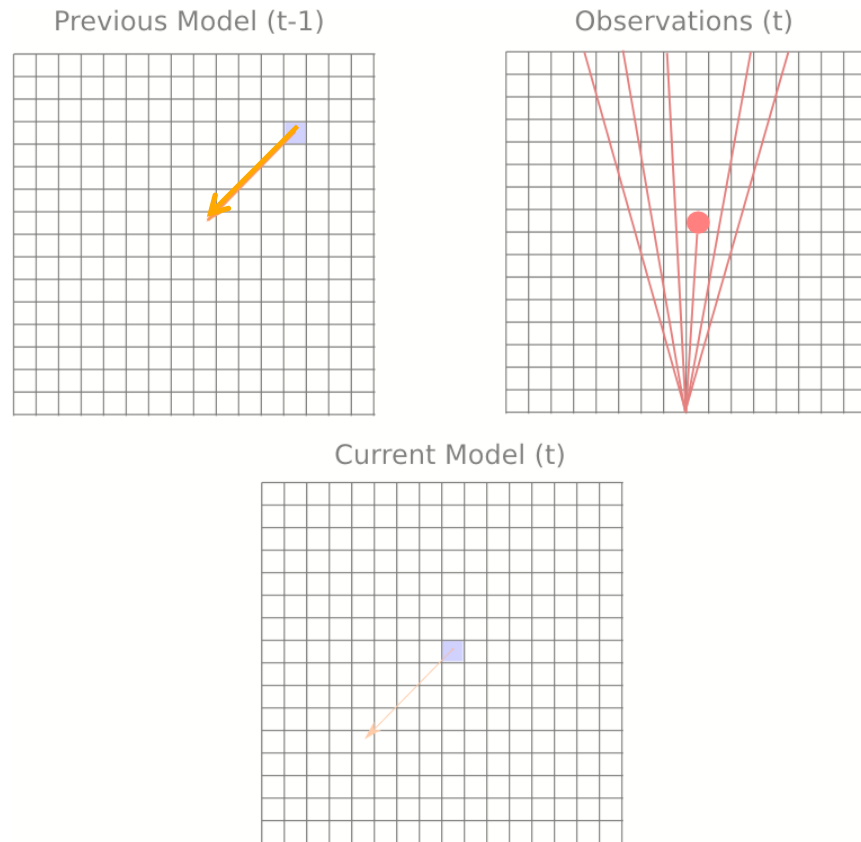
Bayesian Occupancy Filter – Formalism

Variables:

- C : current cell
- A : antecedent cell, i.e. the cell from which the occupancy of the current cell comes from
- O : occupancy of the current cell C
- O^{-1} : previous occupancy in the antecedent cell
- V : current velocity
- **V^{-1} : previous velocity in the antecedent A (time $t-1$)**
- Z : observations (sensor data)

Objective:

- $P(O V | Z C)$: probability of occupancy & velocity, knowing the cell location & the observations



Bayesian Occupancy Filter – Formalism

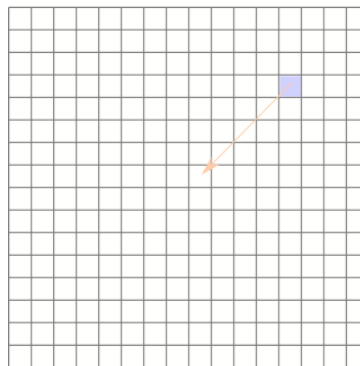
Variables:

- C : current cell
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- O : occupancy of the current cell C
- O^{-1} : previous occupancy in the antecedent cell
- V : current velocity
- V^{-1} : previous velocity in the antecedent
- **Z : observations (sensor data) at time t**

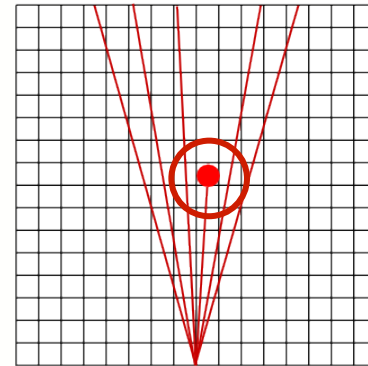
Objective:

- $P(O \ V \ | \ Z \ C)$: probability of occupancy & velocity, knowing the cell location & the observations

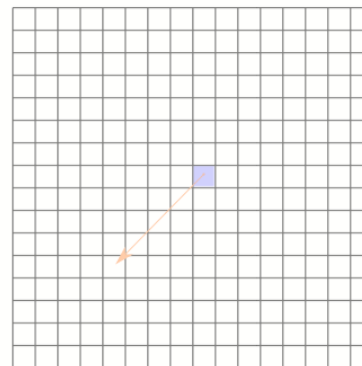
Previous Model (t-1)



Observations (t)



Current Model (t)



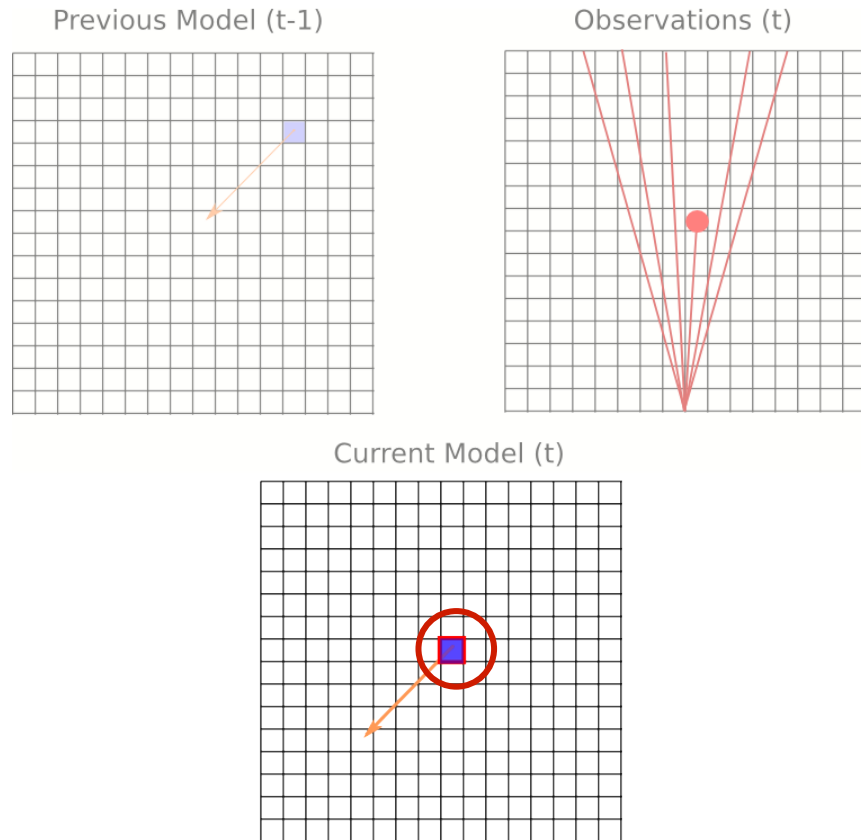
Bayesian Occupancy Filter – Formalism

Variables:

- C : current cell
- A : antecedent cell, i.e. the cell from which the occupancy of the current cell comes from
- O : occupancy of the current cell C
- O^{-1} : previous occupancy in the antecedent cell
- V : current velocity
- V^{-1} : previous velocity in the antecedent
- Z : observations (sensor data)

Objective:

- Evaluate $P(O \ V \mid Z \ C)$: Probability of **Occupancy & Velocity** for each cell C , knowing the **observations Z** and the cell **location C** in the grid



Bayesian Occupancy Filter – How to theoretically compute $P(O V | Z C)$?

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

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

The joint probability term can be re-written as follows:

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

Joint probability
 => used for the update of $P(O V | Z C)$

Bayesian Occupancy Filter – How to theoretically compute $P(O V | Z C)$?

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

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

$$P(C A O O^{-1} V V^{-1} Z) = \underbrace{P(A)}_{\text{Selected as uniform}} \underbrace{P(O^{-1} V^{-1} | A)}_{\text{uniform}} \underbrace{P(O V | O^{-1} V^{-1})}_{\text{uniform}} \underbrace{P(C | A V)}_{\text{uniform}} \underbrace{P(Z | O C)}_{\text{uniform}}$$

$P(A)$: Selected as uniform

\Rightarrow every cell can a priori be an antecedent of C

Bayesian Occupancy Filter – How to theoretically compute $P(O V | Z C)$?

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

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

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

$P(O^{-1} V^{-1} | A)$: Result from the previous iteration

Bayesian Occupancy Filter – How to theoretically compute $P(O V | Z C)$?

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

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

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

$P(O V | O^{-1} V^{-1})$: *Dynamic model*

Bayesian Occupancy Filter – How to theoretically compute $P(O V | Z C)$?

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

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

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

$P(C | A V)$: Indicator function of the cell C corresponding to the “projection” in the grid of the antecedent A at a given velocity V

Bayesian Occupancy Filter – How to theoretically compute $P(O V | Z C)$?

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

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

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

$\mathbf{P(Z | O C)}$: *Sensor model*

Bayesian Occupancy Filter – *Main properties*

- **Bayesian Filtering Method** for implementing the DP-Grid formalism
=> *Occupancy probability & Velocity probability*
- **Integrates raw sensor data** into a coherent model of the environment
- **Highly parallelizable** framework
- Allow to construct **Static Map** & to extract **Motion Field**. It also allow to perform conservative short-term motion prediction => *see session 7*

