Dynamic Occlusion Reasoning for Dense Urban Autonomous Driving

1. Mathematical Formulation

1.1 Probabilistic Occupancy
Each grid cell maintains a probability of being occupied:

$P(c_i = 1 \mid z_{1:t})$

where c_i represents occupancy of cell i and z denotes sensor observations.

1.2 Bayesian State Estimation
Hidden agents are modeled using recursive Bayesian filtering:

$P(x_t \mid z_{1:t}) \propto P(z_t \mid x_t) \int P(x_t \mid x_{t-1}) P(x_{t-1} \mid z_{1:t-1}) dx$

This allows belief propagation even when agents are occluded.

1.3 Collision Risk Estimation
Expected collision risk is computed as:

$R = \Sigma P_e \cdot P_i$

where P_e is the probability of existence of a hidden agent and P_i is the probability of trajectory intersection.

2. System Architecture Design

Overall Pipeline

Sensor Inputs (Camera, LiDAR, Radar)
↓
Sensor Fusion & BEV Transformation
↓
Occlusion Detection Module
↓
Probabilistic Occupancy & Belief Tracker
↓
Hidden Agent Prediction (CVAE / Motion Models)
↓
Risk-Aware Planning & Control

Module Responsibilities

• Perception Module: Detects visible agents and occluders
• Occlusion Reasoner: Identifies hidden regions and assigns priors

- Prediction Module: Generates multi-modal trajectories
- Planner: Optimizes safety-aware cost functions under uncertainty
- Controller: Executes smooth, defensive maneuvers

3. Integration with Autonomous Stack

The occlusion reasoning module interfaces directly with the prediction and planning layers, influencing speed profiles, lane changes, and stopping behavior in dense urban scenarios.

4. Conclusion

Incorporating mathematical reasoning and structured architecture enables autonomous systems to anticipate unseen hazards. Dynamic Occlusion Reasoning bridges the gap between perception uncertainty and safe decision-making.