Inferring Occluded Agent Behavior in Dynamic Games from Noise Corrupted Observations

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Abstract

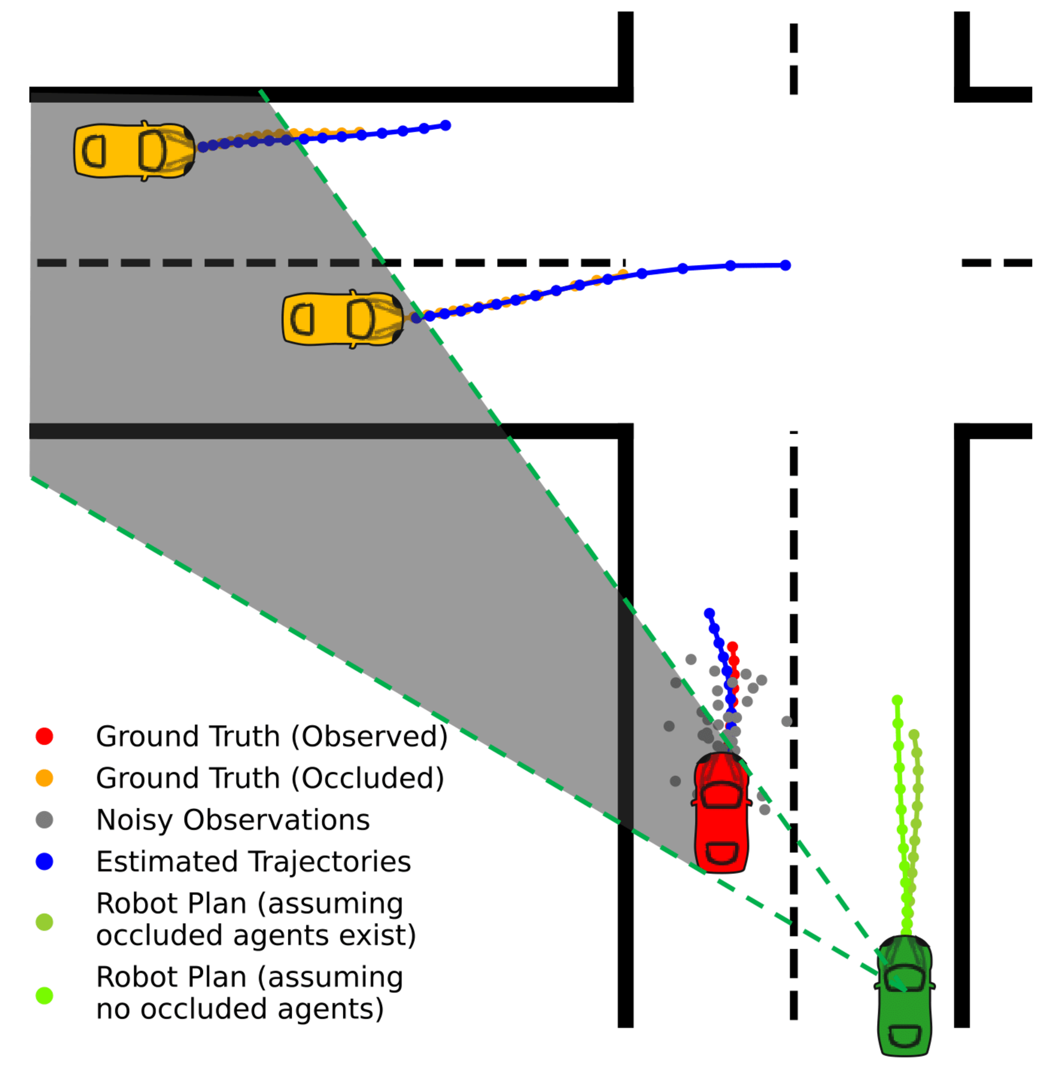
Challenges:

Game-theoretic planning frameworks can model multi-agent interactions but often require full observability of all participants, and therefore, struggle in traffic scenarios where occlusions are common.

Main Contributions: We propose

(i) an occlusion-aware game-theoretic inference method that jointly infers the states and intentions of both visible and potentially occluded agents using only noisy observations.

(ii) a receding horizon planning framework based on an occlusion-aware contingency game, dealing with uncertainty of the existence of occluded agents during navigation.



Preliminaries

Finite-horizon, discrete-time Nash game:

$$\min_{\mathbf{x}^i,\mathbf{u}^i} J^i(\mathbf{x},\mathbf{u};\mathbf{w}^i), \ i \in [M],$$

$$\text{s.t. } x^i_{k+1} = f(x^i_k, u^i_k), \ k \in [T].$$

Open-loop Nash Equilibrium (OLNE):

$$J^i(\mathbf{x}^*,\mathbf{u}^*;\mathbf{w}^i) \le J^i(\mathbf{x}^i,\mathbf{x}^{-i*},\mathbf{u}^i,\mathbf{u}^{-i*};\mathbf{w}^i), \ i \in [M]$$

First-Order Necessary (KKT) Conditions:

$$\mathbf{G}(\mathbf{x},\mathbf{u},\boldsymbol{\lambda}^i;\mathbf{w}^i) = \begin{bmatrix} \nabla_{\mathbf{x}^i}\mathcal{L}^i(\mathbf{x},\mathbf{u},\boldsymbol{\lambda}^i;\mathbf{w}^i) \\ \nabla_{\mathbf{u}^i}\mathcal{L}^i(\mathbf{x},\mathbf{u},\boldsymbol{\lambda}^i;\mathbf{w}^i) \\ x^i_{k+1} - f(x^i_k,u^i_k), \ k \in [T] \end{bmatrix} = \mathbf{0}, \ i \in [M]$$

Lagrangian:

$$\mathcal{L}^i(\mathbf{x},\mathbf{u},\boldsymbol{\lambda}^i;\mathbf{w}^i) = J^i(\mathbf{x},\mathbf{u};\mathbf{w}^i) + \sum_{k=0}^{T-1} {\lambda^i_k}^\top (x^i_{k+1} - f(x^i_k,u^i_k))$$

Occlusion-aware game-theoretic Inference

Key Features:

(i) Encodes the OLNE condition via KKT conditions.

(ii) Relies on noisy-corrupted observations of visible agents only.

(iii) Estimates all agents' states $\mathbf{x}$ and intentions $\mathbf{w}$ simultaneously.

Least Square Estimator:

$$\min_{\mathbf{w},\mathbf{x},\mathbf{u},\boldsymbol{\lambda}} \frac{1}{|\mathcal{V}|\cdot T}\sum_{k=0}^{T-1}\sum_{j\in\mathcal{V}} \left\| y^j_k - [I_2 \ \ \mathbf{0}]\, x^j_k \right\|_2^2,$$

$$\text{s.t. } \mathbf{G}(\mathbf{x}^i,\mathbf{u}^i,\boldsymbol{\lambda}^i;\mathbf{w}^i) = \mathbf{0}, \ i \in [M].$$

Occlusion-aware contingency game

In the ego Agent i's contingency game:

Agent i minimizes weighted cost of both hypotheses θ_1, θ_2.

$$\min_{\mathbf{x}^i_{\theta,i},\mathbf{u}^i_{\theta,i}} \sum_{\theta\in\Theta} b(\theta) J^i_{\theta,i}(\mathbf{x},\mathbf{u};\mathbf{w}^i)$$

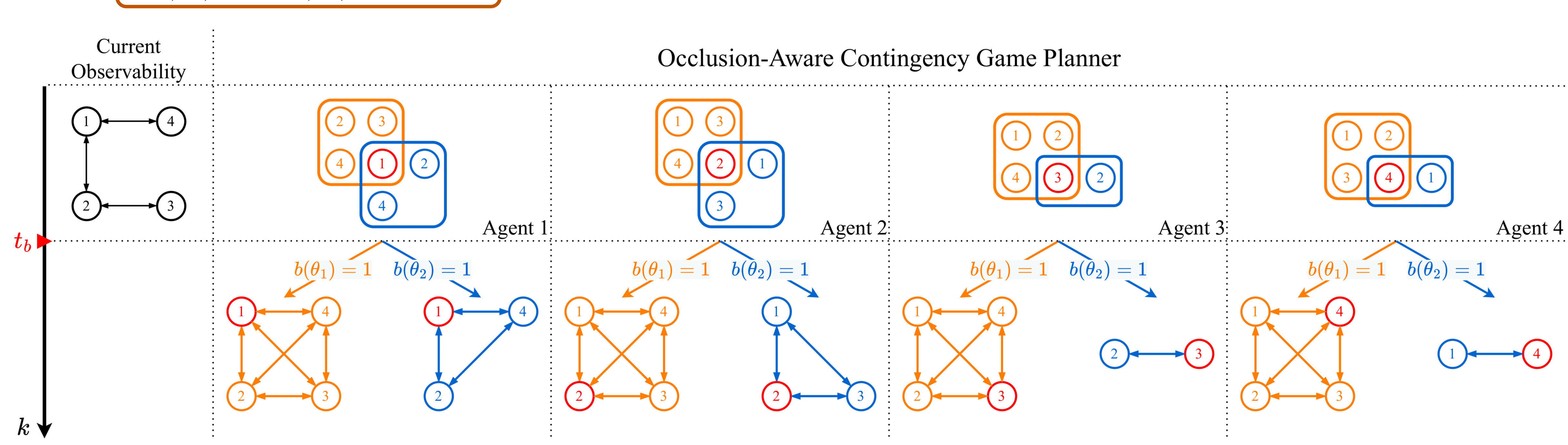
$$\text{s.t. } x^i_{k+1;\theta,i} = f(x^i_{k;\theta,i}, u^i_{k;\theta,i}), \ k \in [T],$$

$$u^i_{k;\theta_1,i} = u^i_{k;\theta_2,i}, \ k < t_b. \quad \text{Contingency constraint}$$

Agent j minimize their respective cost for each θ.

$$\min_{\mathbf{x}^j_{\theta,i},\mathbf{u}^j_{\theta,i}} J^j_{\theta,i}(\mathbf{x},\mathbf{u};\mathbf{w}^j)$$

$$\text{s.t. } x^j_{k+1;\theta,i} = f(x^j_{k;\theta,i}, u^j_{k;\theta,i}), \quad k \in [T]$$



Occlusion-aware contingency game planner actively prepares for the potentially existing occluded agents before the presence of occluded agents is confirmed at t_b.

Receding Horizon Estimation and Planning:

Algorithm 1 Receding Horizon Estimation and Planning Pipeline in an Occlusion-Aware Contingency Game

Input: receding horizon game $\Gamma_{\text{RH}}(\mathbf{w},\mathbf{x}_0,f)$, receding horizon contingency game $\Gamma_{\text{con,RH}}(\Theta,t_b,\mathbf{w},\mathbf{x}_0,f)$, trajectory observation $\mathbf{y}^{\mathcal{V}_i}$, game horizon T, observation interval K, branching time t_b.

Output: Agent i's control sequence in receding horizon $\mathbf{u}^i_{\text{RH}} = \{u^i_{k|k}\}^{\infty}_{k=K}$.

1: **for** $k = K$ to ∞ **do**

2: $\hat{\mathbf{w}}^{-i}, \hat{\mathbf{x}}^{-i}_k \leftarrow$ solving the maximum likelihood problem given in (11). [Estimation]

3: $u^{i*}_{k|k} \leftarrow$ solving $\Gamma_{\text{con,k}}(\Theta,t_b,\mathbf{w}^i,\hat{\mathbf{w}}^{-i},x^i_k,\hat{\mathbf{x}}^{-i}_k,f)$ given by (9) and (10). [Planning]

4: $x^i_{k+1} \leftarrow f(x^i_k, u^{i*}_{k|k})$ by state update (1b).

5: **end for**

Experimental Results

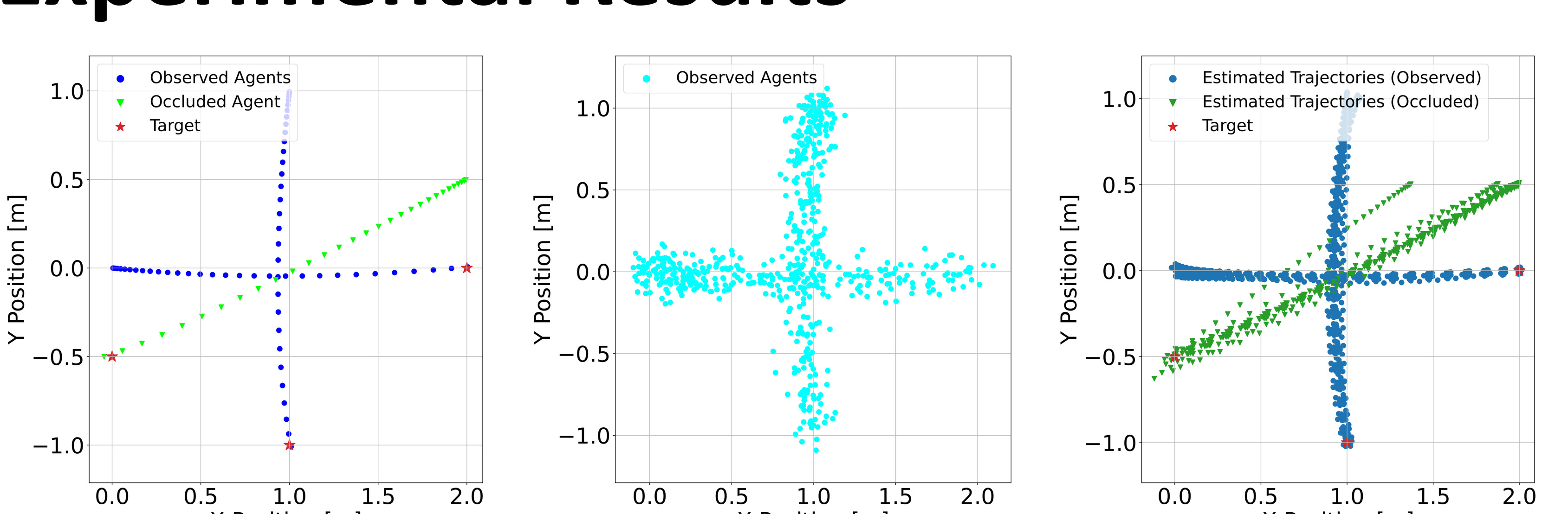


Fig 1: 3 agent interaction scenario

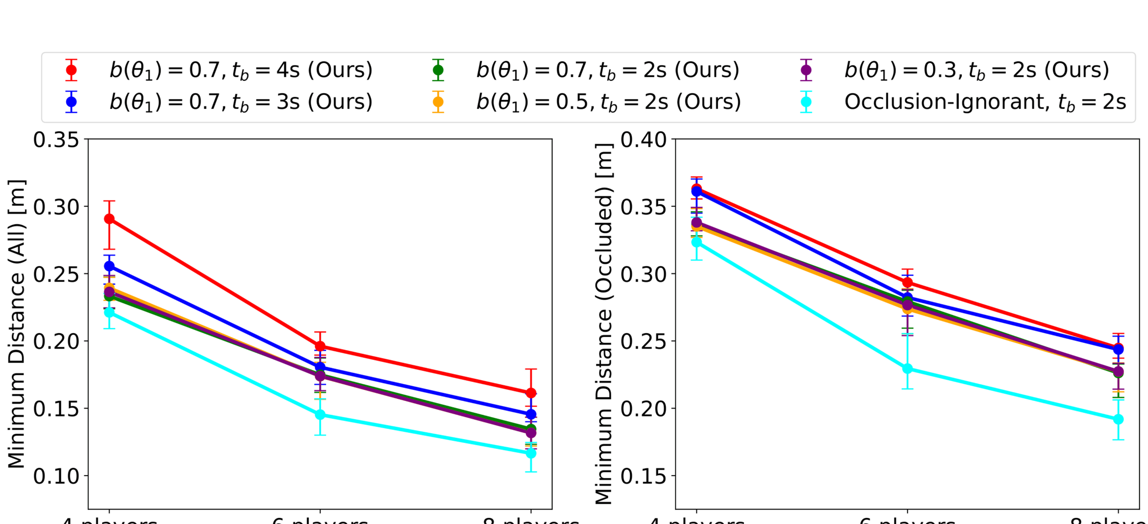


Fig 3: Planning safety results in 4/6/8 agent scenarios

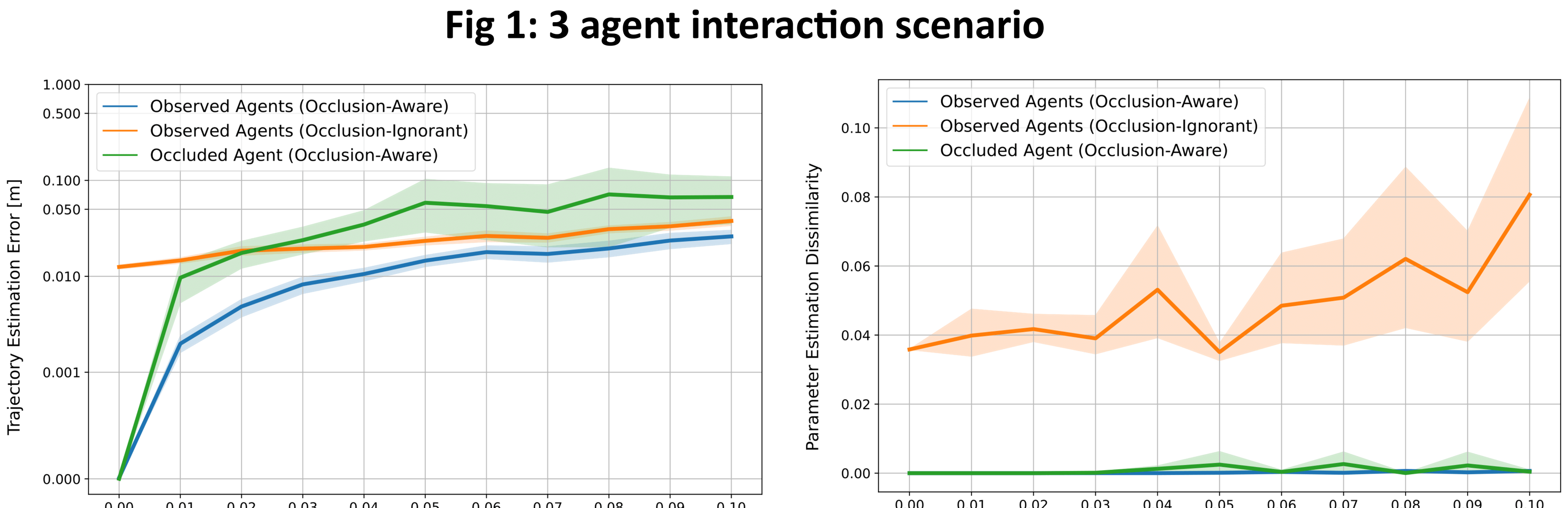


Fig 2: Parameter and trajectory estiamtion results

	occlusion-aware estimator contingency game planner **(ours)**	occlusion-ignorant game estimator and planner **(baseline)**
$\text{ADE}_{\text{observed}}$ [m]	**0.41** / **0.58** / 1.08	0.57 / 0.69 / **0.99**
$\text{ADE}_{\text{occluded}}$ [m]	**0.51** / **0.80** / **1.18**	- [2]
$d_{\text{min, observed}}$ [m]	**1.35** / **1.36** / **1.42**	1.25 / 1.27 / 1.32
$d_{\text{min, occluded}}$ [m]	**4.61** / **4.67** / **4.68**	3.66 / 3.70 / 4.58

Table 1: Estimation and planning safety results in a crossing road scenario

Highlights:

(i) The proposed occlusion-aware inference method estimates the occluded agent's state and infer all agents' intention from noisy observations of visible agents only (Fig 1) with higher estimation accuracy (Fig 2).

(ii) The proposed receding horizon estimation and planning framework outperforms in estimation accuracy and planning safety (Fig 3 and Table 1).