Autonomous Platooning of General Connected Vehicles Using Bayesian Receding Horizon Control

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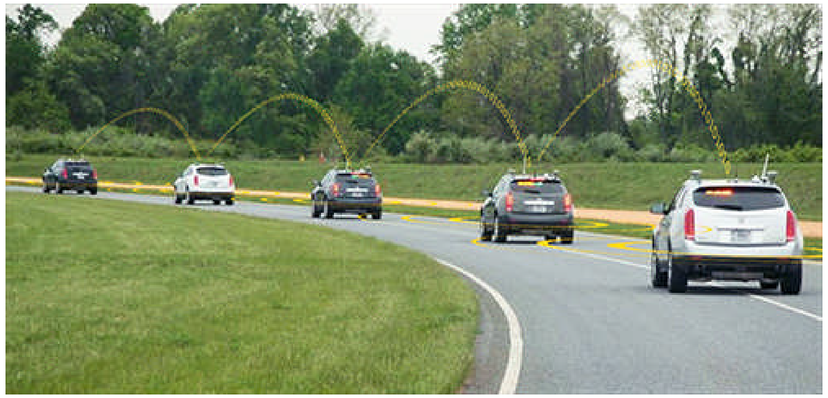
Autonomous Platooning and Autonomous Following

Benefits of autonomous platooning

- Reduction of drivers;
- Reduction of traffic accident;
- Reduction of traffic jam;
- Emission of CO_2.

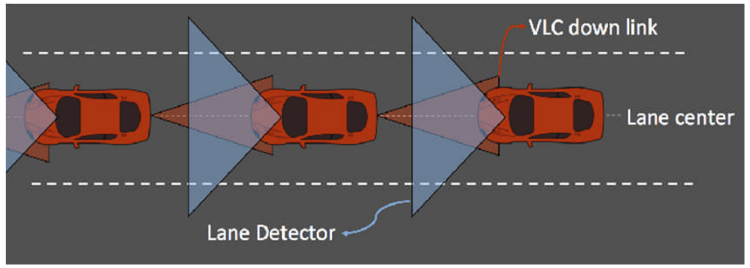
Autonomous platooning

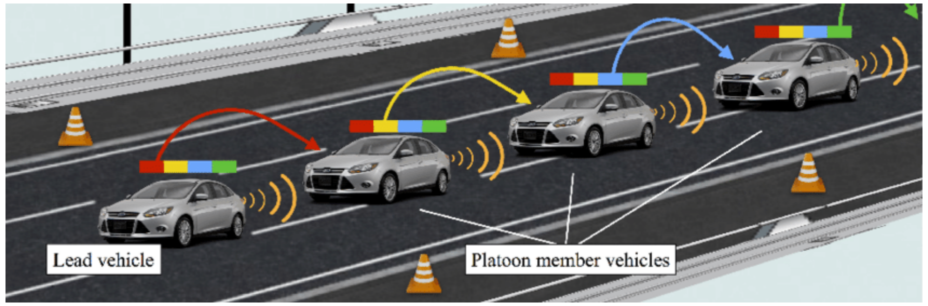
- Autonomous driving (leader vehicle)
  - Autonomy fails at some point.
  - Applies to only leader vehicle.
- Autonomous following (follower vehicles)
  - Easier task
  - Applies to all following vehicles.



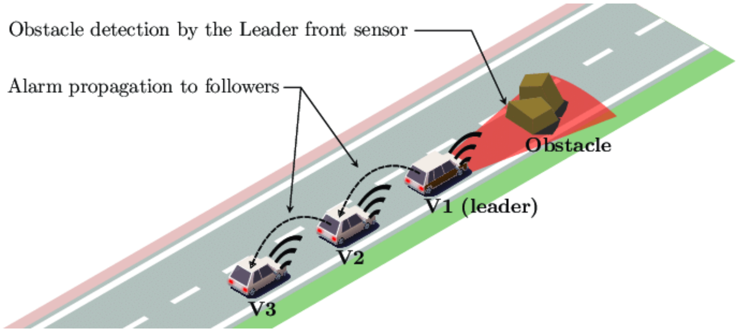
Past Work on Autonomous Following

- Autonomous following on public roads [Assidiq, et al, 2008]
  - Lane detection
  - Distance minimization in confined space
- Multi-robot cooperation with communication
  - Formation control: Centralized
  - Leader-follower approach: Autonomous following
    - Path planning [Madhevan, et al, 2013]
    - Trajectory planning [Gasparetto, et al, 2015]
    - Replanning with communication [Wu, et al, 2018]





Autonomous following with communication has been proposed only with an autonomous leader vehicle.



Autonomous following with communication

Objectives

- Develop an autonomous following technique with communication when a leader vehicle is manually driven;
- Demonstrate and validate the efficacy of the proposed technique.

Outline

Motion and Sensor Models of Leader and Follower Vehicles

Outline

Recursive Bayesian Estimation and Receding Horizon Control

Proposed autonomous following

Experimental validation

Conclusions and future work

Motion Models

Leader vehicle: Control is unknown

$$\mathbf{x}_k^l = \mathbf{f}^l\left(\mathbf{x}_{k-1}^l, \mathbf{w}_k^l\right)$$

Follower vehicle: Control is autonomous

$$\mathbf{x}_k^f = \mathbf{f}^f\left(\mathbf{x}_{k-1}^f, \mathbf{u}_k^f, \mathbf{w}_k^f\right)$$

Sensor Model

Sensor on follower vehicle

$${}^f\mathbf{z}_k^l = {}^f\mathbf{h}^l\left(\mathbf{x}^l, \mathbf{x}_k^f, {}^f\mathbf{v}_k^l\right)$$

k: Time step
l: Leader vehicle
f: Follower vehicle

$\mathbf{x}_k^{(\cdot)}$: State
$\mathbf{u}_k^{(\cdot)}$: Control
$\mathbf{w}_k^{(\cdot)}$: Motion noise
${}^f\mathbf{z}_k^l$: Observation of l by f
${}^f\mathbf{v}_k^l$: Observation noise

The leader's state may be observable, but its intention may not be unknown.

Recursive Bayesian Estimation

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Initial guess $p\left(\mathbf{x}_0^l \mid \tilde{\mathbf{x}}_0^f\right)$

$p(\cdot)$: Probability density representing belief

$\tilde{\mathbf{x}}_k^f$: Instance of follower state (follower state is assumed to be known)

Prediction

$$\boxed{p\left(\mathbf{x}_k^l \mid {}^f\tilde{\mathbf{z}}_{1:k-1}^l, \tilde{\mathbf{x}}_{1:k-1}^f\right)} = \int_{\mathcal{X}^l} p\left(\mathbf{x}_k^l \mid \mathbf{x}_{k-1}^l\right) \boxed{p\left(\mathbf{x}_{k-1}^l \mid {}^f\tilde{\mathbf{z}}_{1:k-1}^l, \tilde{\mathbf{x}}_{1:k-1}^f\right)} d\mathbf{x}_{k-1}^l$$

$p\left(\mathbf{x}_k^l \mid \mathbf{x}_{k-1}^l\right)$: Motion model

Correction

$$\boxed{p\left(\mathbf{x}_k^l \mid {}^f\tilde{\mathbf{z}}_{1:k}^l, \tilde{\mathbf{x}}_{1:k}^f\right)} = \frac{l\left(\mathbf{x}_k^l \mid {}^f\tilde{\mathbf{z}}_k^l, \tilde{\mathbf{x}}_k^f\right) \boxed{p\left(\mathbf{x}_k^l \mid {}^f\tilde{\mathbf{z}}_{1:k-1}^l, \tilde{\mathbf{x}}_{1:k-1}^f\right)}}{\int_{\mathcal{X}^l} l\left(\mathbf{x}_k^l \mid {}^f\tilde{\mathbf{z}}_k^l, \tilde{\mathbf{x}}_k^f\right) \boxed{p\left(\mathbf{x}_k^l \mid {}^f\tilde{\mathbf{z}}_{1:k-1}^l, \tilde{\mathbf{x}}_{1:k-1}^f\right)} d\mathbf{x}_k^l}$$

$l\left(\mathbf{x}_k^l \mid {}^f\tilde{\mathbf{z}}_{k-1}^l\right)$: Observation likelihood from sensor model

Prediction

$p\left(\mathbf{x}_k^l \mid {}^f\mathbf{z}_{1:k-1}^l, \mathbf{x}_{1:k-1}^f\right)$

Correction

$p\left(\mathbf{x}_k^l \mid {}^f\mathbf{z}_{1:k}^l, \mathbf{x}_{1:k}^f\right)$

k -> k-1

Conventional Autonomous Following

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Observation based

$$J\left(l\left(\mathbf{x}_k^l|^f\tilde{\mathbf{z}}_k^l,\tilde{\mathbf{x}}_k^f\right)\right) = \left\|\mathbf{g}\left(l\left(\mathbf{x}_k^l|^f\tilde{\mathbf{z}}_k^l,\tilde{\mathbf{x}}_k^f\right)\right)-\left(\mathbf{x}_{k+1}^f+\mathbf{d}_k\right)\right\|_2 \to \min_{\mathbf{u}_{k+1}^f}$$

where $\mathbf{x}_{k+1}^f=\mathbf{f}^f\left(\tilde{\mathbf{x}}_k^f,\mathbf{u}_{k+1}^f,\tilde{\mathbf{w}}_{k+1}^f\right)$

Prediction based (Receding Horizon Control; RHC) **without communication**

$$J\left(p\left(\mathbf{x}_{k+n_c}^l|^f\tilde{\mathbf{z}}_{1:k}^l,\tilde{\mathbf{x}}_{1:k}^f\right)\right) = \left\|\mathbf{g}\left(p\left(\mathbf{x}_{k+n_c}^l|^f\tilde{\mathbf{z}}_{1:k}^l,\tilde{\mathbf{x}}_{1:k}^f\right)\right)-\left(\tilde{\mathbf{x}}_{k+n_c}^f+\mathbf{d}_k\right)\right\|_2 \to \min_{\mathbf{u}_{k+1:k+n_c}^f}$$

where $p\left(\mathbf{x}_{k+\kappa}^l|^f\tilde{\mathbf{z}}_{1:k}^l,\tilde{\mathbf{x}}_{1:k}^f\right)=\int_{\mathcal{X}^l} p\left(\mathbf{x}_{k+\kappa}^l|\mathbf{x}_{k+\kappa-1}^l\right)p\left(\mathbf{x}_{k+\kappa-1}^l|^f\tilde{\mathbf{z}}_{1:k}^l,\tilde{\mathbf{x}}_{1:k}^f\right)d\mathbf{x}_k^l,$

$$\mathbf{x}_{k+\kappa}^f=\mathbf{f}^f\left(\tilde{\mathbf{x}}_{k+\kappa-1}^f,\mathbf{u}_{k+\kappa}^f,\tilde{\mathbf{w}}_{k+\kappa}^f\right)\quad\forall\kappa\in\{1,\ldots,n_c\}$$

Following is determined only from the leader's state.

Proposed Autonomous Following with Vehicle Connection

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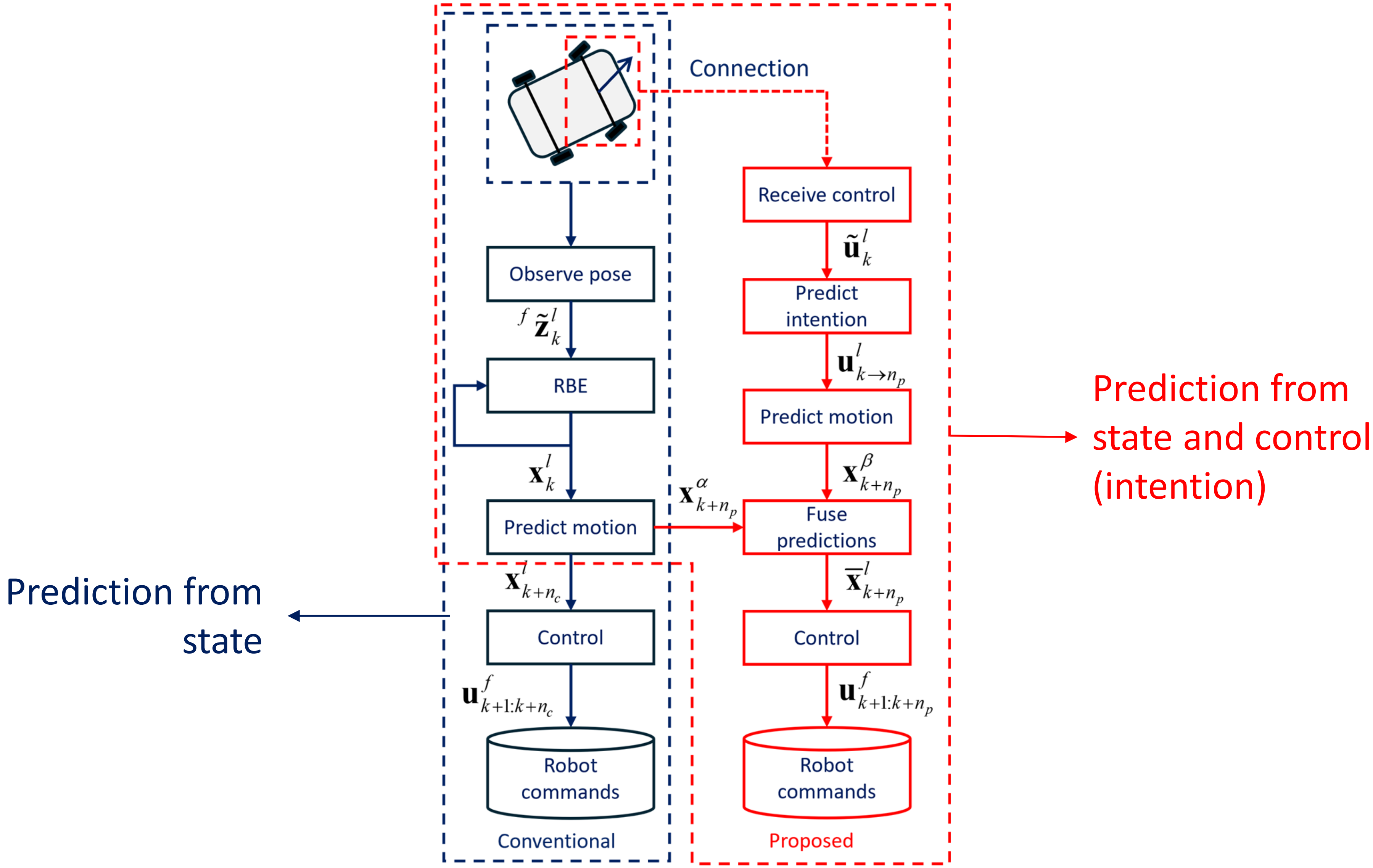

Non-Gaussian Prediction with Gaussian Sensor Fusion

Outline

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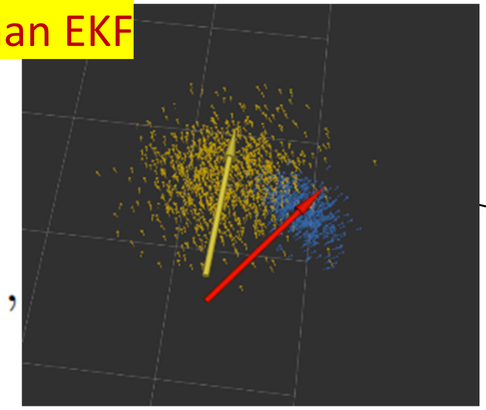
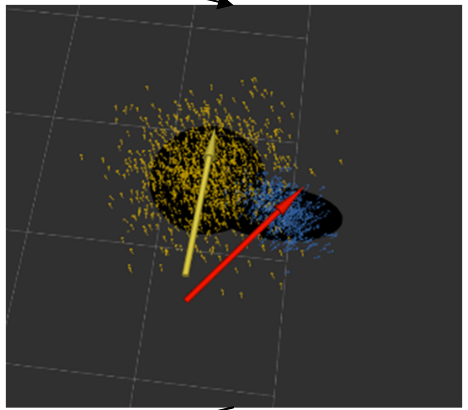
1. Prediction by particle filter

More accurate than EKF

Without control $\mathbf{x}^{\alpha,i}_{k+\kappa+1} = \mathbf{f}^{\alpha}\left(\mathbf{x}^{\alpha,i}_{k+\kappa}, \mathbf{w}^{\alpha,i}_{k}\right),$

With control $\mathbf{x}^{\beta}_{k+\kappa,i} = \mathbf{f}^{\beta}\left(\mathbf{x}^{\beta,i}_{k+\kappa-1}, \mathbf{u}^{\beta,i}_{k\to n_p}, \mathbf{w}^{\beta,i}_{k}\right),$





2. Gaussian approximation

Valid as noise is Gaussian

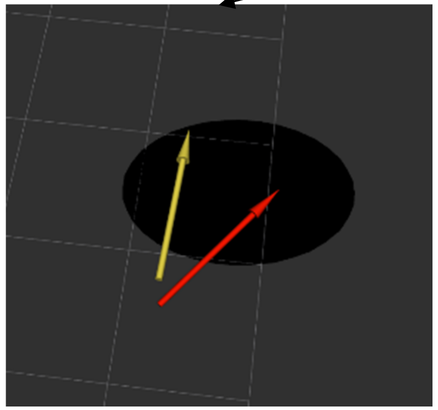
$$\overline{\mathbf{x}}^{t(\cdot)}_{k+n_k} = \frac{1}{N}\sum_{i=1}^{N}\mathbf{x}^{t(\cdot),i}_{k+n_k}$$

$$\mathbf{\Sigma}^{t(\cdot)}_{k+n_k} = \frac{1}{N}\sum_{i=1}^{N}\left(\mathbf{x}^{t(\cdot),i}_{k+n_k} - \overline{\mathbf{x}}^{t(\cdot)}_{k+n_k}\right)\left(\mathbf{x}^{t(\cdot),i}_{k+n_k} - \overline{\mathbf{x}}^{t(\cdot)}_{k+n_k}\right)^{T}$$

3. Gaussian approximation

Gaussian sensor fusion

$$\overline{\mathbf{x}}^{t}_{k+n_k} = \frac{\mathbf{\Sigma}^{th}_{k+n_k}}{\mathbf{\Sigma}^{tn}_{k+n_k} + \mathbf{\Sigma}^{th}_{k+n_k}}\overline{\mathbf{x}}^{tn}_{k+n_k} + \frac{\mathbf{\Sigma}^{tn}_{k+n_k}}{\mathbf{\Sigma}^{tn}_{k+n_k} + \mathbf{\Sigma}^{th}_{k+n_k}}\overline{\mathbf{x}}^{th}_{k+n_k}$$



Experimental Platform

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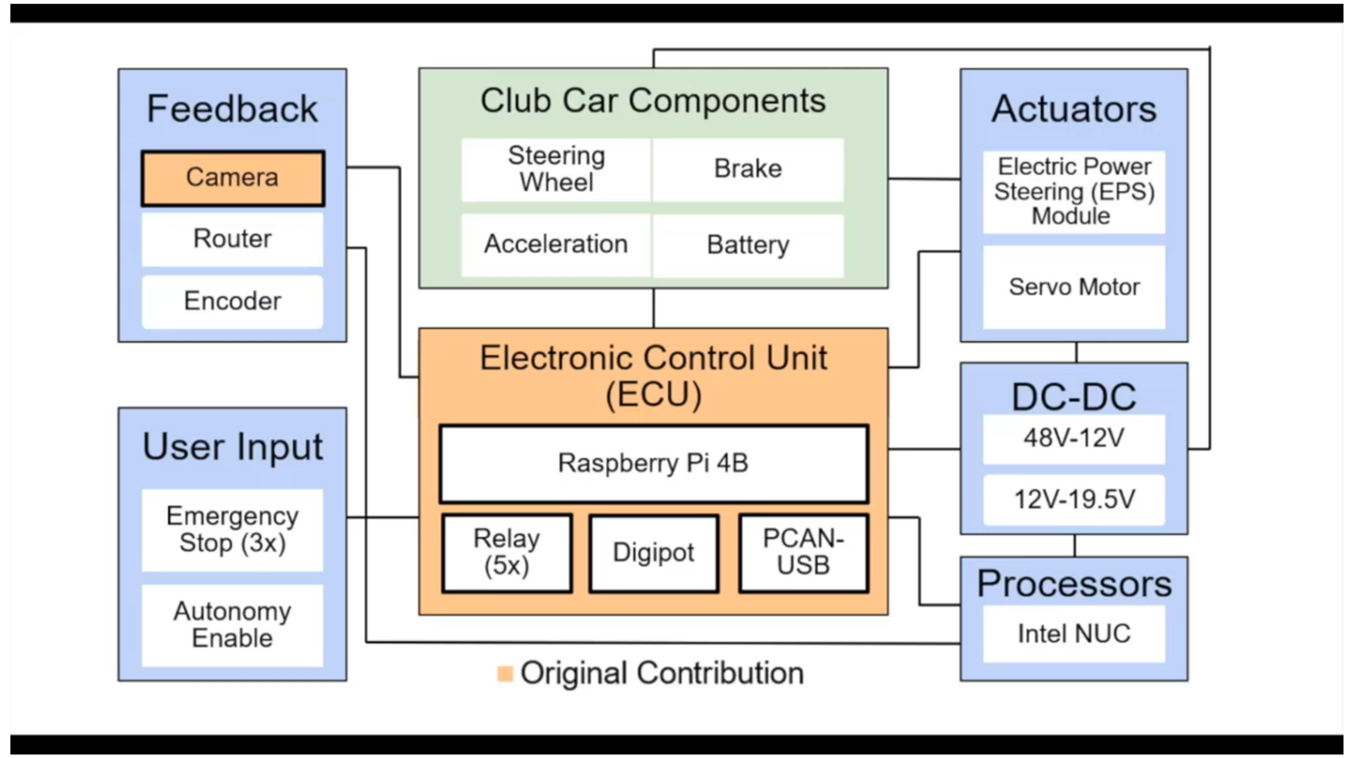
Club Car golf cart



Parameters of autonomous follower

Parameter	Value
L	1.2 [m]
$\bar{v}_k^l$	8.5 [m/s]
d	4 [m]
$\mathbf{\Sigma}_k^{l,u}$	$[0.1, 0, 0, 0.087]$ [,m,m,m]
$\bar{\mathbf{w}}_k^{\alpha}$	$[0.5, 0.5]$ [m,m]
$\mathbf{\Sigma}_k^{\alpha,w}$	$[0.05, 0, 0, 0.017]$ [m,m,m,m]
$\bar{\mathbf{w}}_k^{\beta}$	$[0.5, 0.5]$ [m,m]
$\mathbf{\Sigma}_k^{\beta,w}$	$[0.5, 0, 0, 0.087]$ [m,m,m,m]
N	1000

Proposed Prediction vs. Conventional Prediction

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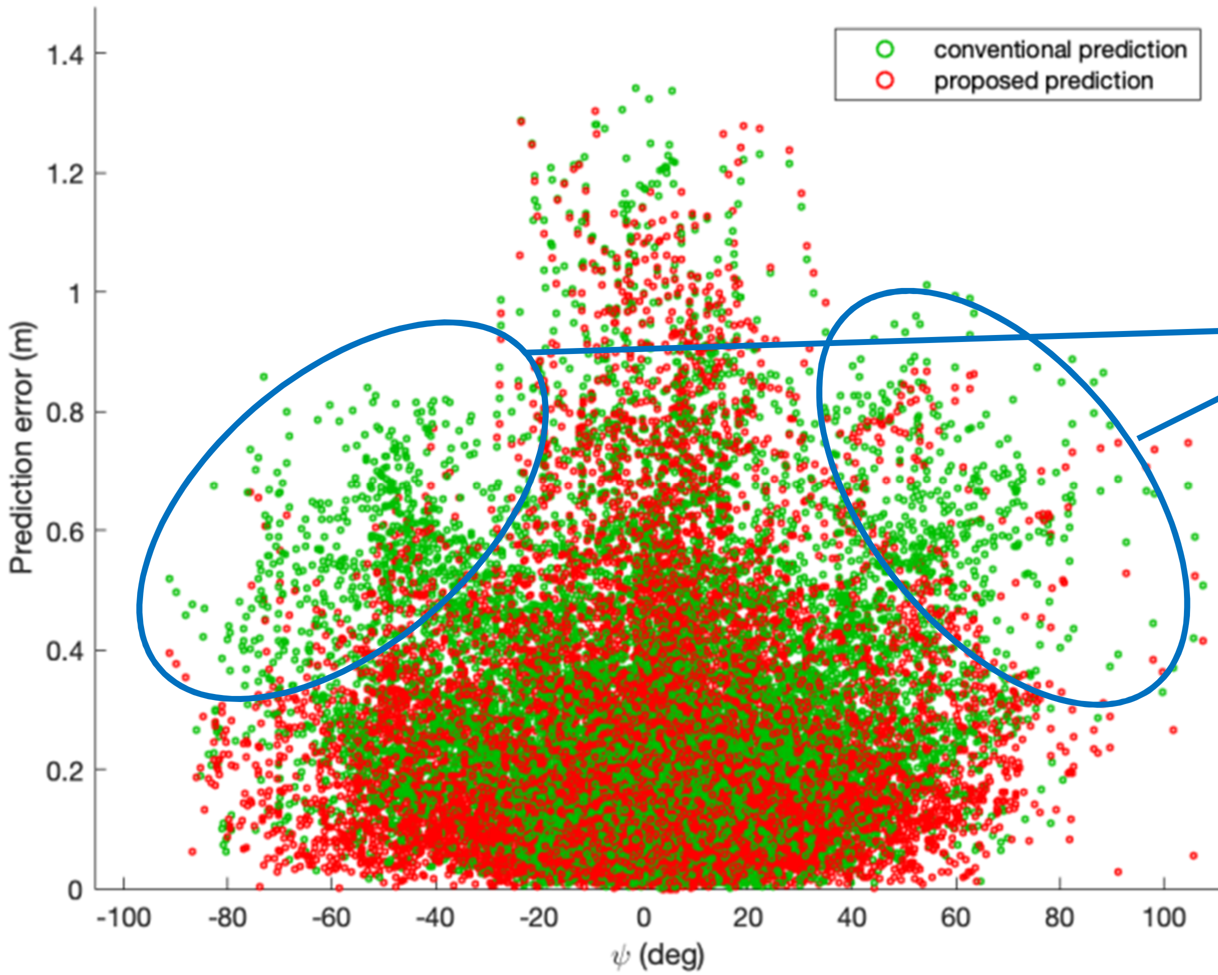

Conventional prediction shows large prediction error when turning

Autonomous Following by Proposed and Conventional

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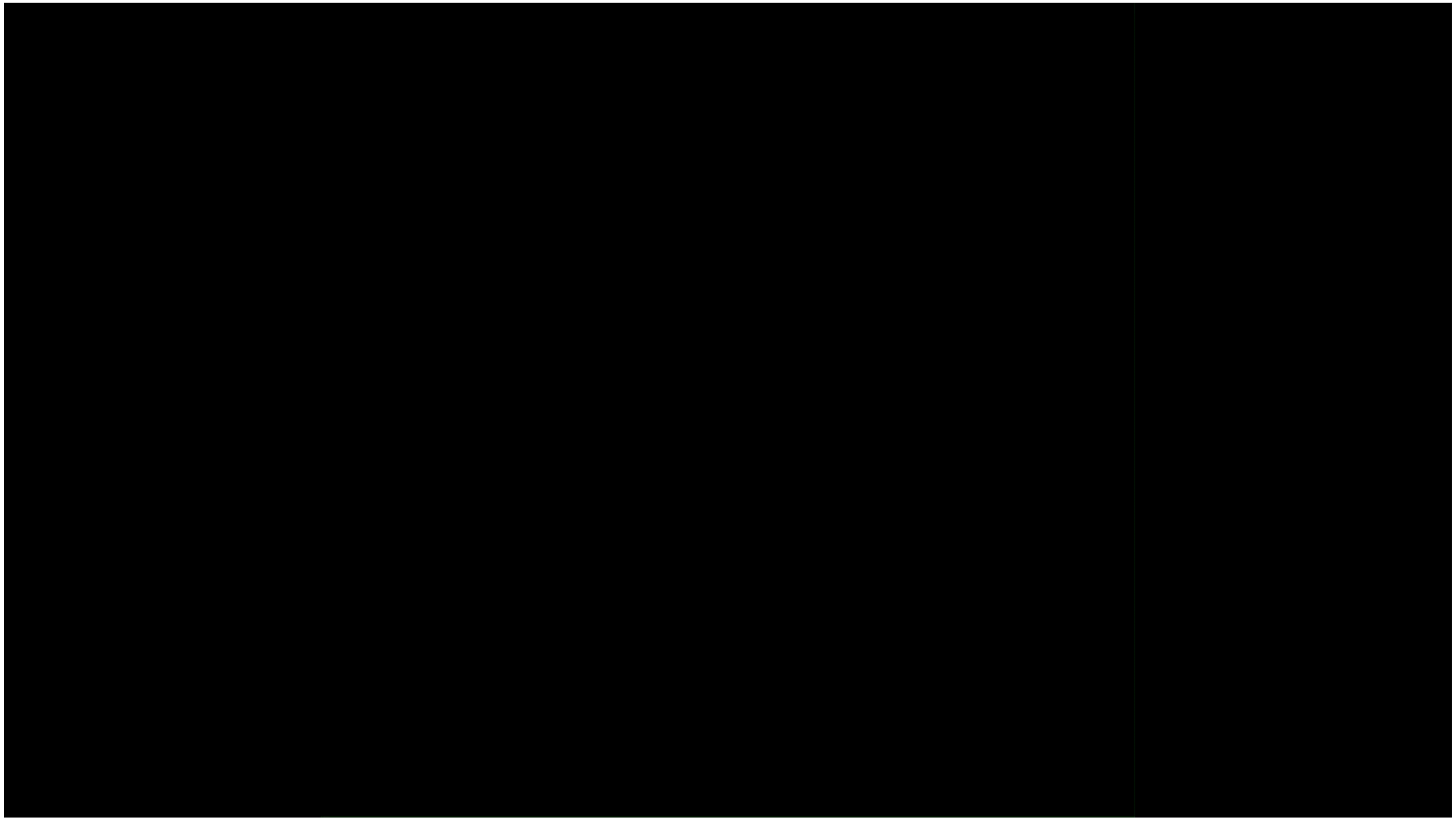

Quantitative Results

Outline

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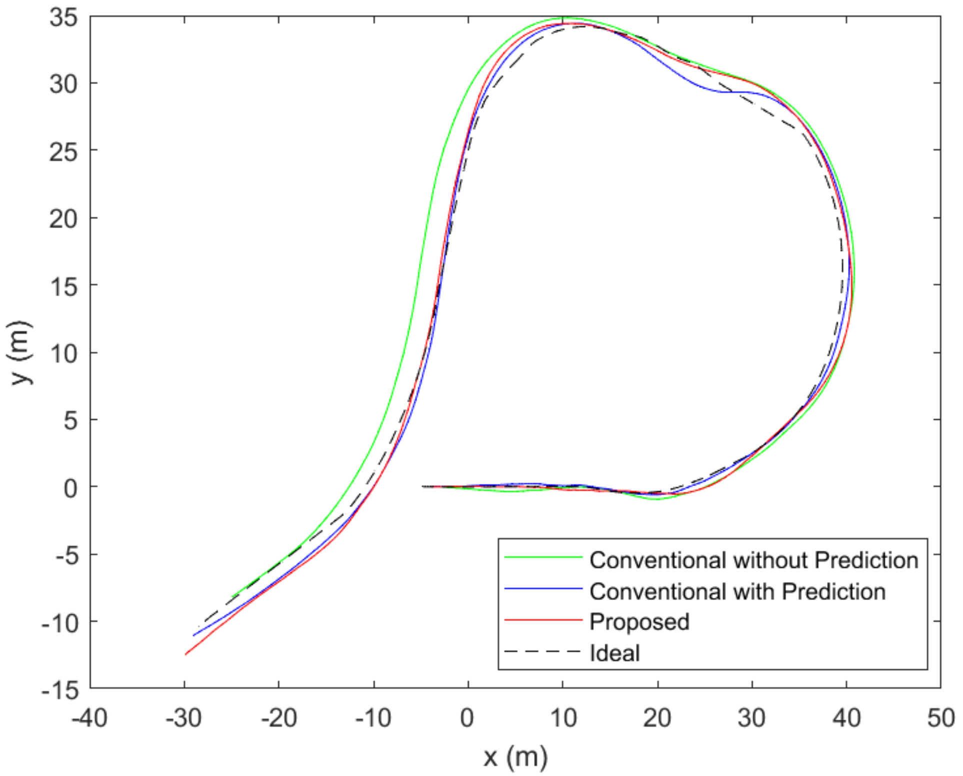
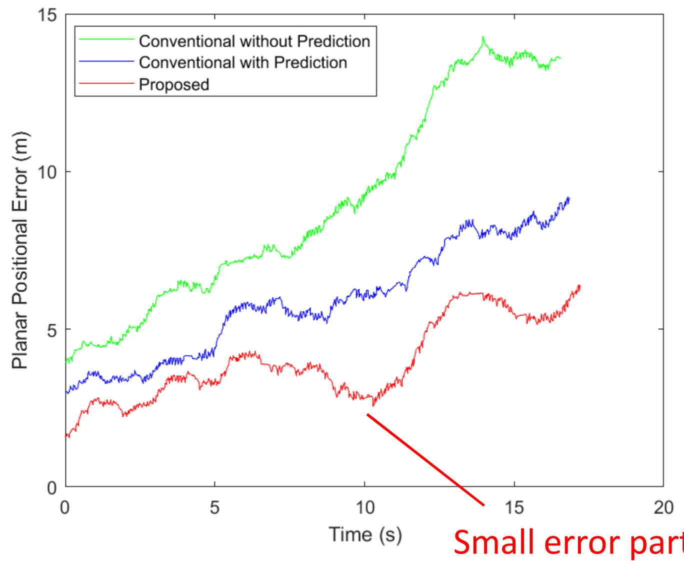


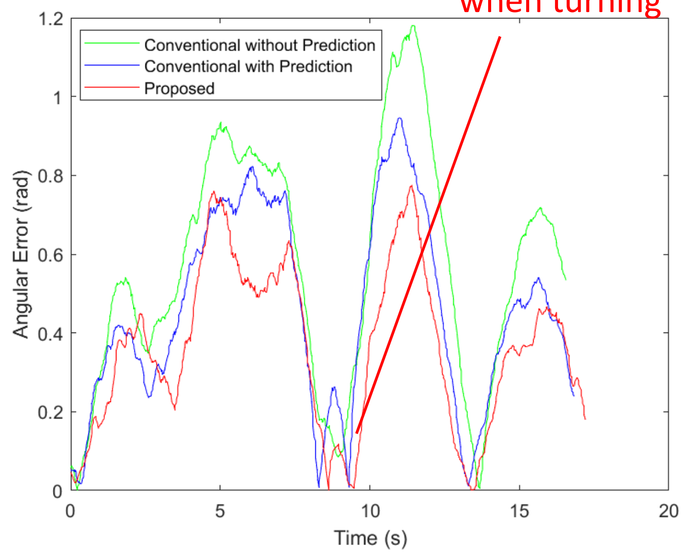
Vehicle path

Position error



Small error particularly when turning

Orientation error



Experimental Validation

Outline

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Conclusions and Future Work

Conclusions

- Incorporation of vehicle connection;
- Fusion of non-holonomic motion and driver's intention
- Experimental validation of effect of incorporation of human intention and its uncertainty

Future work

- Validation with real golf carts
- Incorporation of obstacle and collision avoidance

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THK The Mark of Linear Motion

Members of VICTOR Lab

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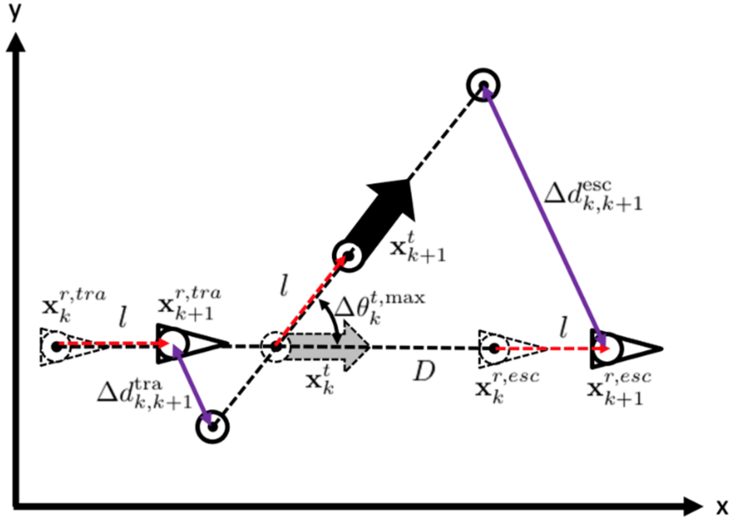
Robotic escorting needs



Difficulty of escorting compared to tracking

[Conte&Furukawa, ICRA, 2021]
[Conte&Furukawa, JFR, 2021]

Rationale
Positional adjustment of escorting (front following) is much more than tracking (following from behind).

Distance to adjust

Track $\Delta d_{k,k+1}^{\mathrm{tra}} = 2(D-l)\sqrt{1-\cos(\theta^{t,\max})}$

Escort $\Delta d_{k,k+1}^{\mathrm{esc}} = 2(D+l)\sqrt{1-\cos(\theta^{t,\max})}$

$$\Delta d_{k,k+1}^{\mathrm{esc}} > \Delta d_{k,k+1}^{\mathrm{tra}}, \forall l > 0 \ \& \ ||\theta^{t,\max}|| \leq \pi/2$$

We Look Where We Walk

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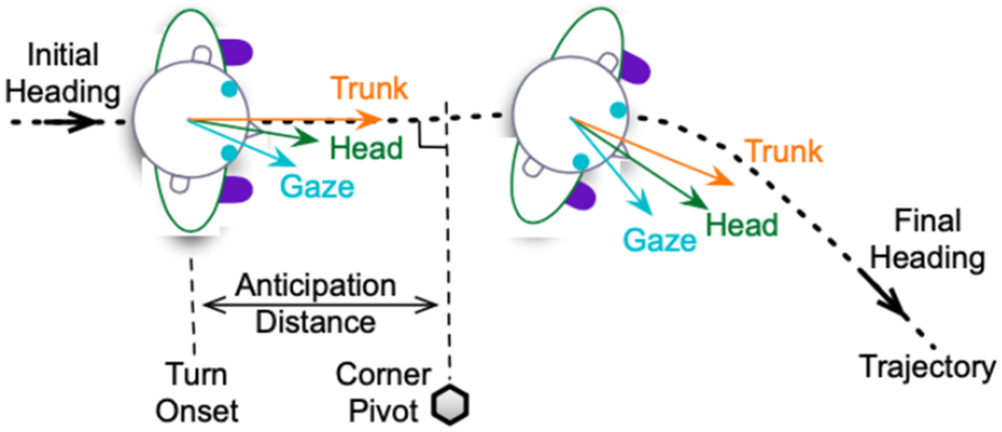
Autonomous robotic escorting



[Lopez et al., 2019]

Incorporation of Intention for Human Pose Prediction

Outline

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Autonomous robotic escorting

- **Conventional prediction** based on observation of human non-holonomic motion

$$\mathbf{x}_{k+1}^{t} = \mathbf{f}^{n}\left(\mathbf{x}_{k}^{t}, \mathbf{w}_{k+1}^{t}\right)$$

$$\rightarrow \mathbf{x}_{k+n_k}^{t} = \mathbf{f}^{n}\left(\mathbf{x}_{k+n_k-1}^{t}, \mathbf{w}_{k+n_k}^{t}\right)$$

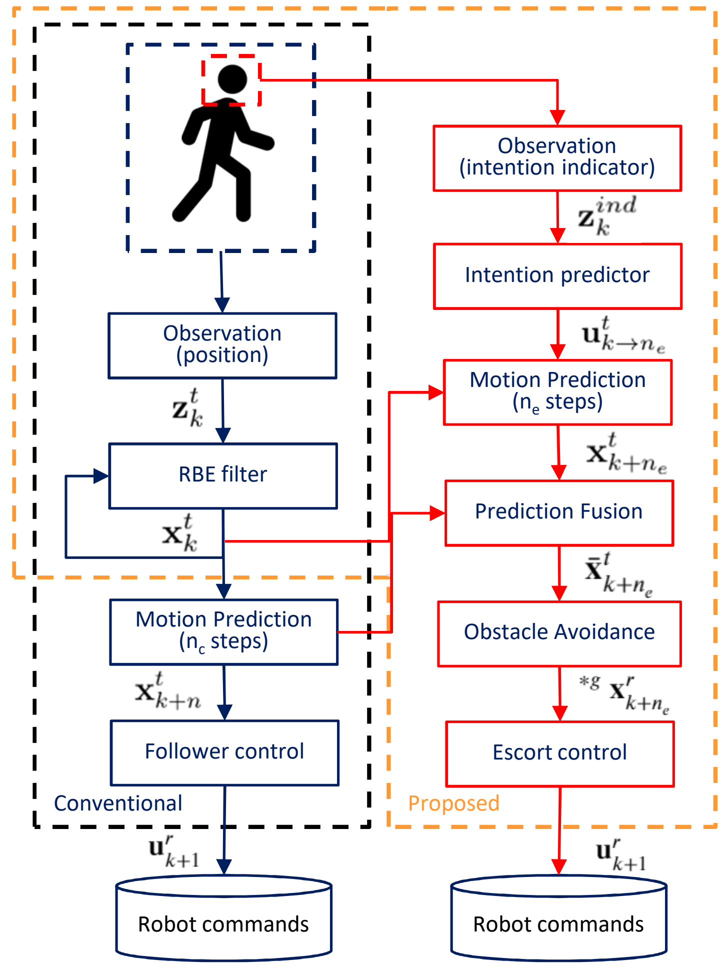
- **Additional prediction** using "intention predictor" with head pose

Intention

$$\mathbf{u}_{k+1\to n_k}^{t} = \mathbf{g}\left(\mathbf{x}_{k}^{t}, \mathbf{x}_{k}^{i}, \mathbf{w}_{k}^{i}\right)$$

$$\mathbf{x}_{k+1}^{t} = \mathbf{f}^{h}\left(\mathbf{x}_{k}^{t}, \mathbf{u}_{k+1\to n_k}^{t}, \mathbf{w}_{k+1}^{t}\right)$$

$$\rightarrow \mathbf{x}_{k+n_k}^{t} = \mathbf{f}^{h}\left(\mathbf{x}_{k+n_k-1}^{t}, \mathbf{u}_{k+1\to n_k}^{t}, \mathbf{w}_{k+n_k}^{t}\right)$$



[Conte & Furukawa, ICRA, 2021]

Escorting Simulation Results

Outline

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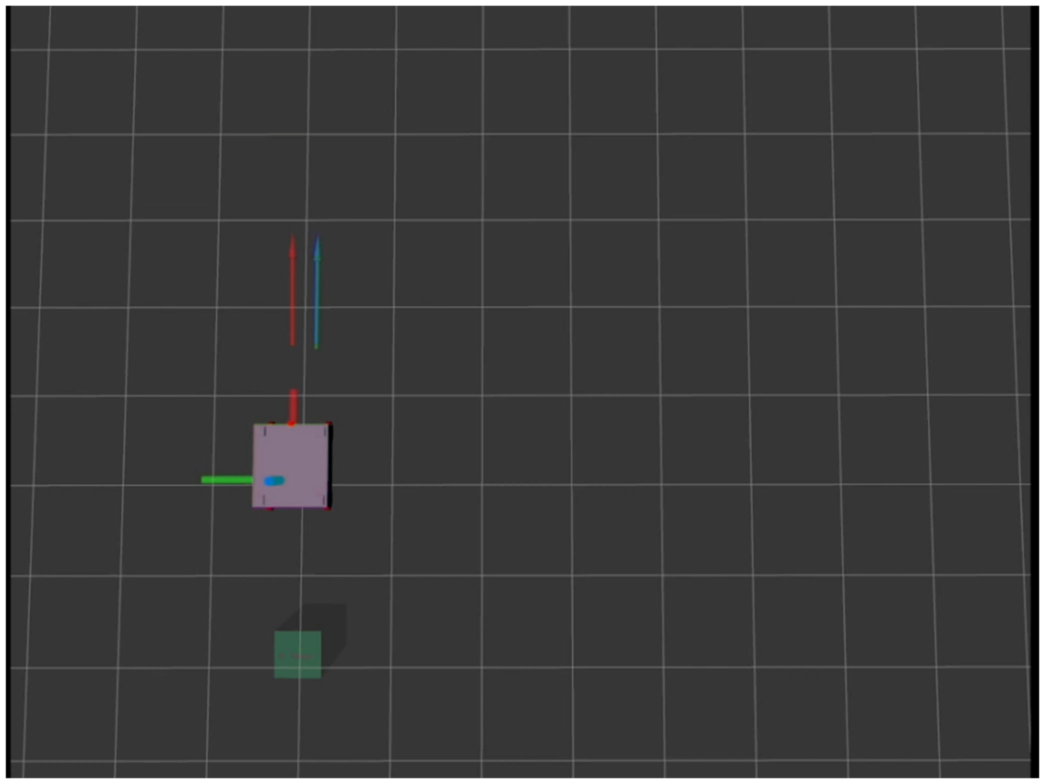
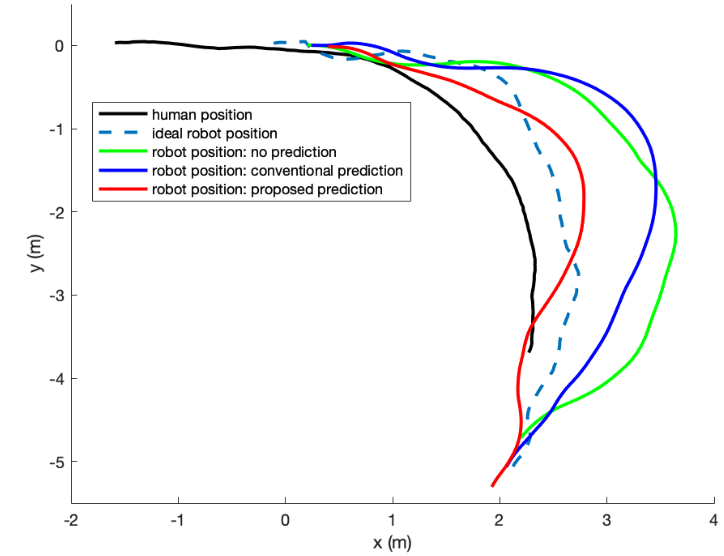
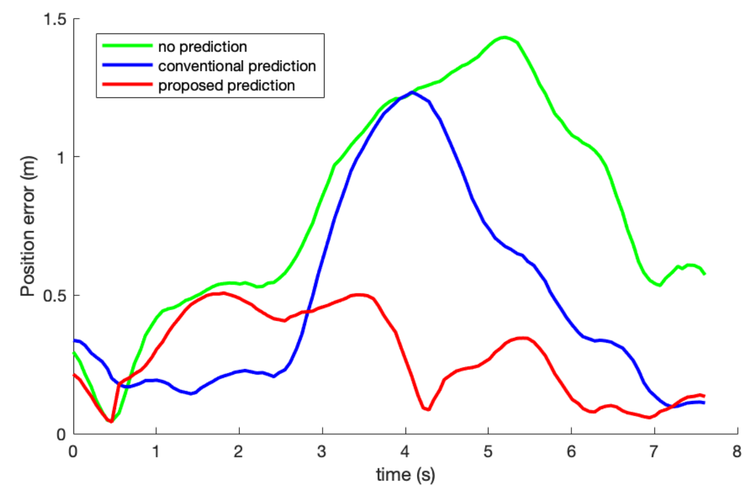
Autonomous robotic escorting

- Comparing proposed method to existing techniques for a single walk path







Real Escorting Results

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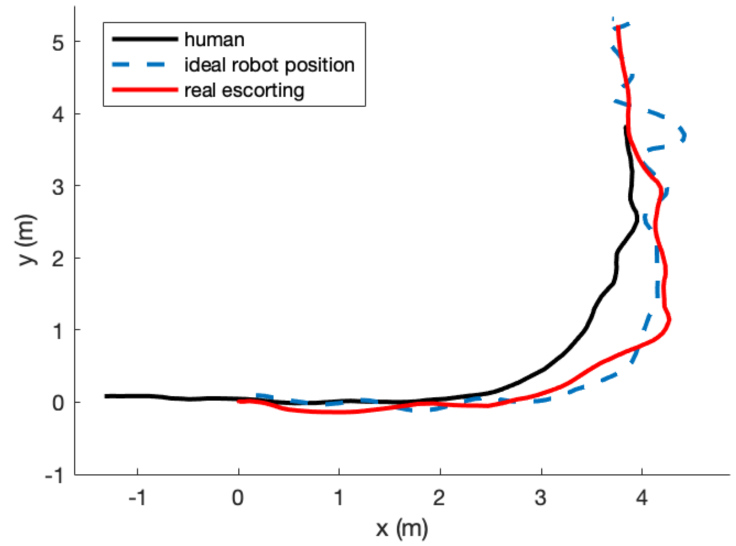
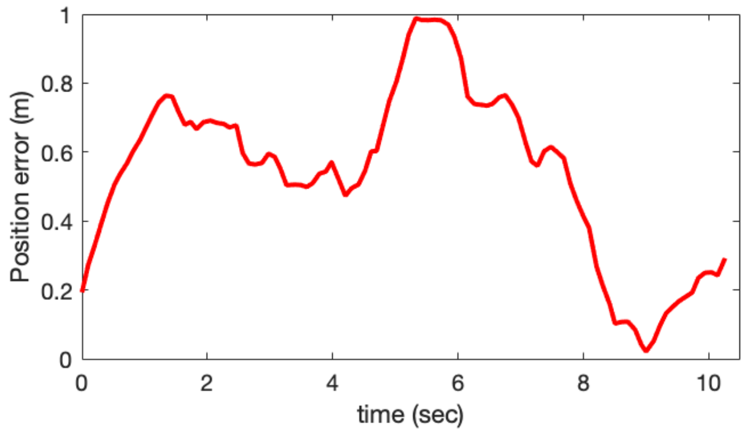
Autonomous robotic escorting

- Successfully escorted at three different walking speeds





Escorting Simulation Results

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- Position error of the robot reduced by 50% the conventional techniques
- A failure rate to 2.9%, a significant reduction from 21.0%