Decentralized Collaborative Navigation with Enhanced Positioning Update for Mobile Robots

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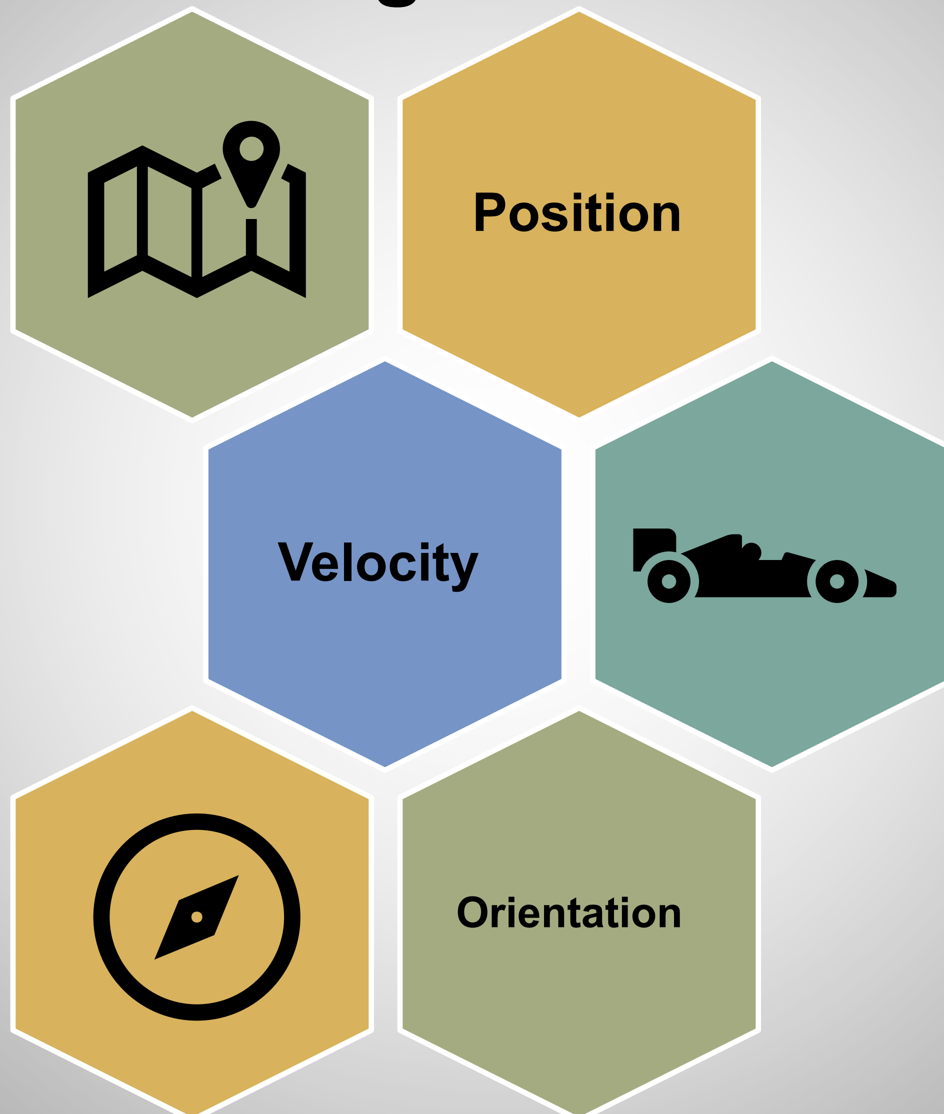
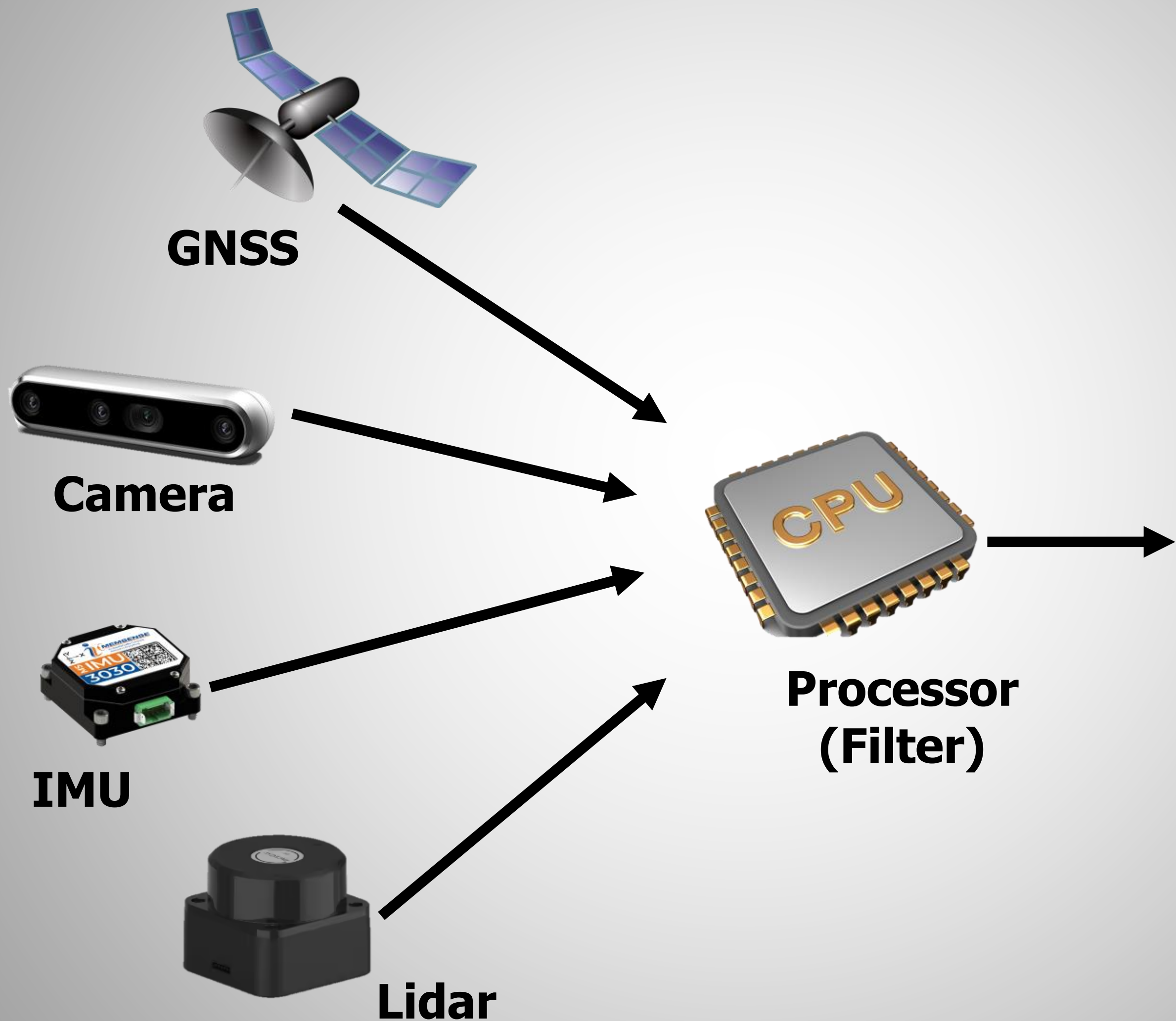
Graduate Students in System and Control – GSC’25

Introduction: Navigation



Introduction: Fusion

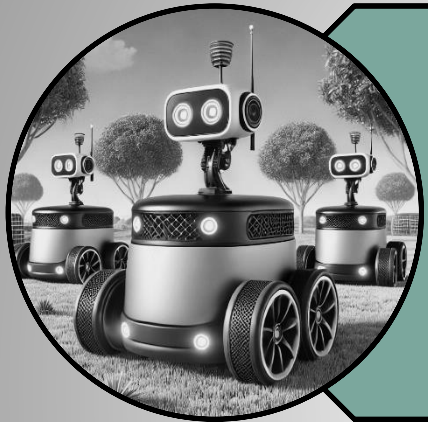


$$x = \begin{bmatrix} p \\ v \\ \psi \end{bmatrix}$$

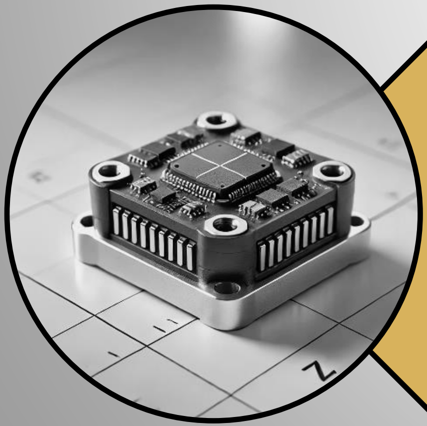
State vector

Introduction: Collaborative Navigation

Motivation



Leverage data from all agents in the environment to enhance positioning accuracy.



Reduce costs by integrating a mix of sensor grades across agents.

Novelty

Scalability:
Decentralized architecture for improved autonomy

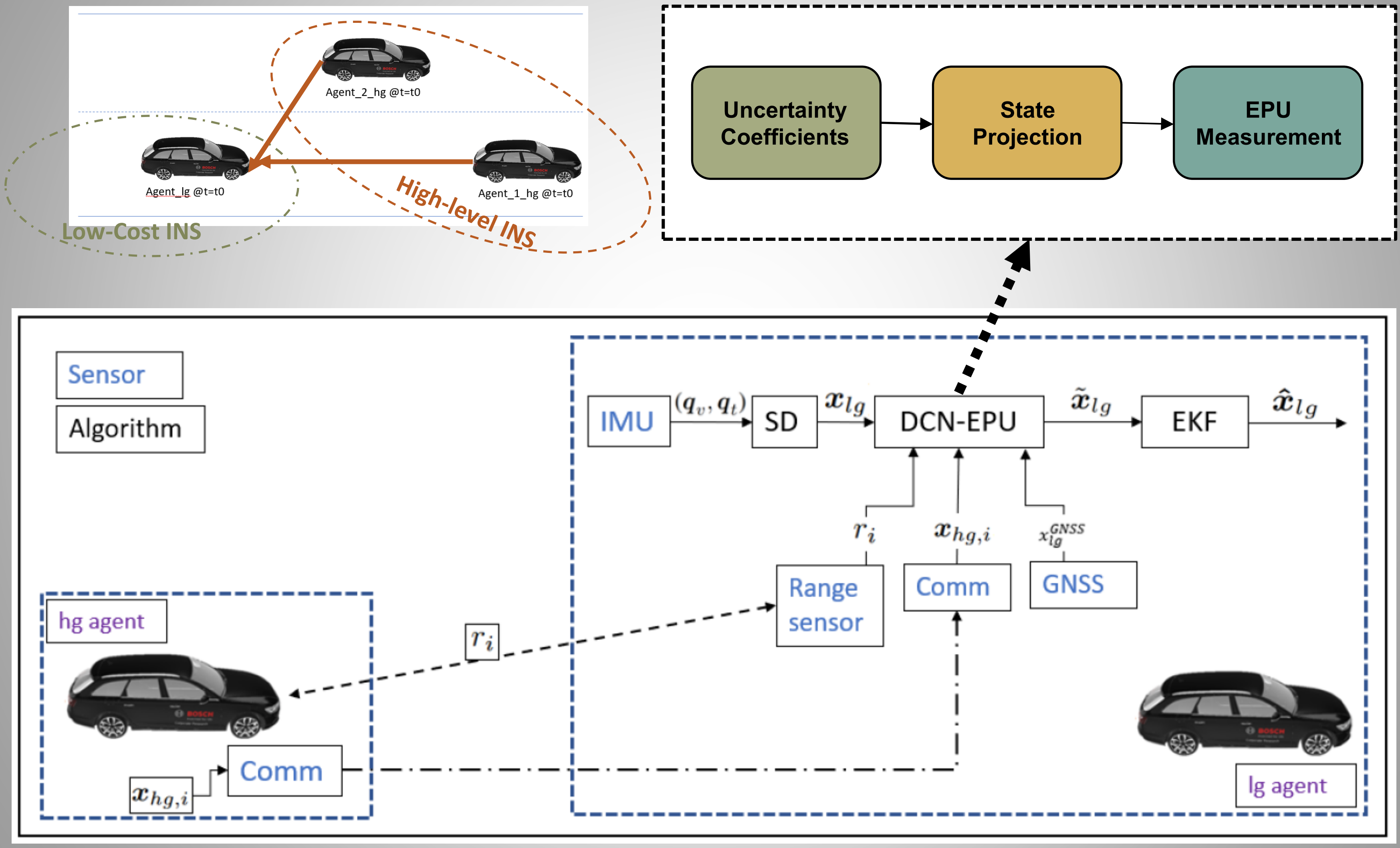
Cost Effective:
Utilizes only range sensors for positioning

Communication:
Minimizes data broadcasting to reduce communication overhead

Computational Cost:
Highly scalable for diverse environments and agent numbers

Miron, Y., Etzion, A., Goldfracht, Y., Di Castro, D., & Klein, I. (2024). Decentralized collaborative navigation with enhanced positioning update for mobile robots. ***IEEE Transactions on Intelligent Vehicles***.

Method: Scheme

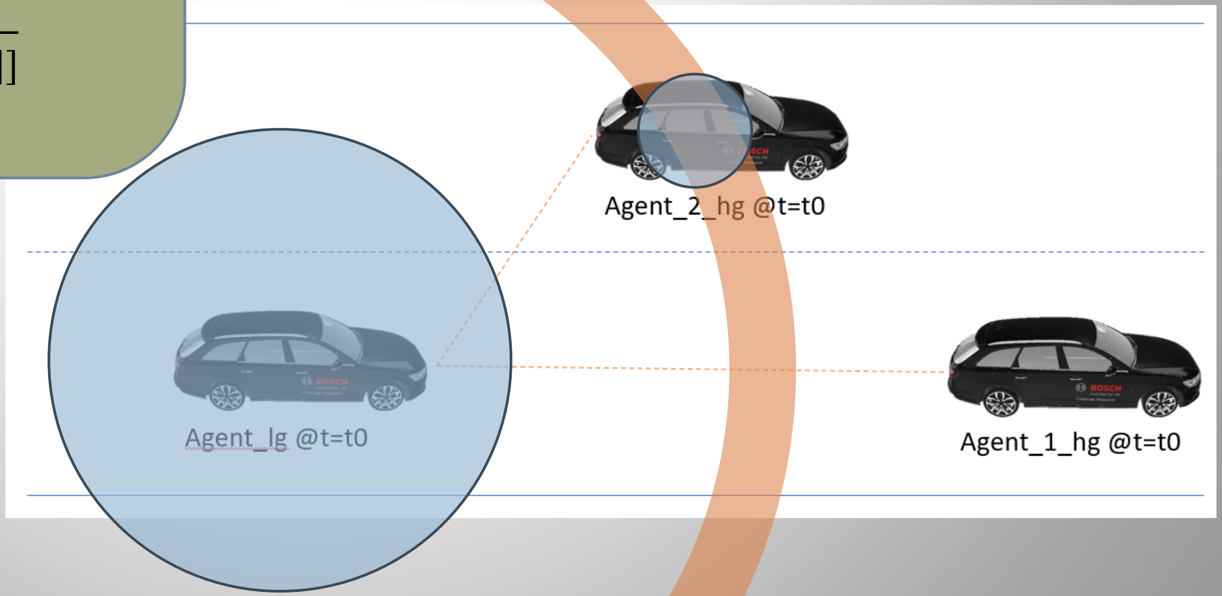


Method: Uncertainty Coefficients

$$\beta_0 = \frac{1}{\sigma_{lg}}, \beta_i = \frac{1}{a_1 r_i + a_2 \sigma_{hg,i}}, i = 1, \ldots, N$$

$$\vec{\beta} = \left(\sum_{i=0}^{N} \beta_i \right)^{-1} \vec{\beta}$$

$$\alpha = \frac{2}{N} \frac{\sigma_r}{\sigma_r + \vec{\beta} \cdot [|\sigma_{lg}|, |\overrightarrow{\sigma_{hg}}|]}$$

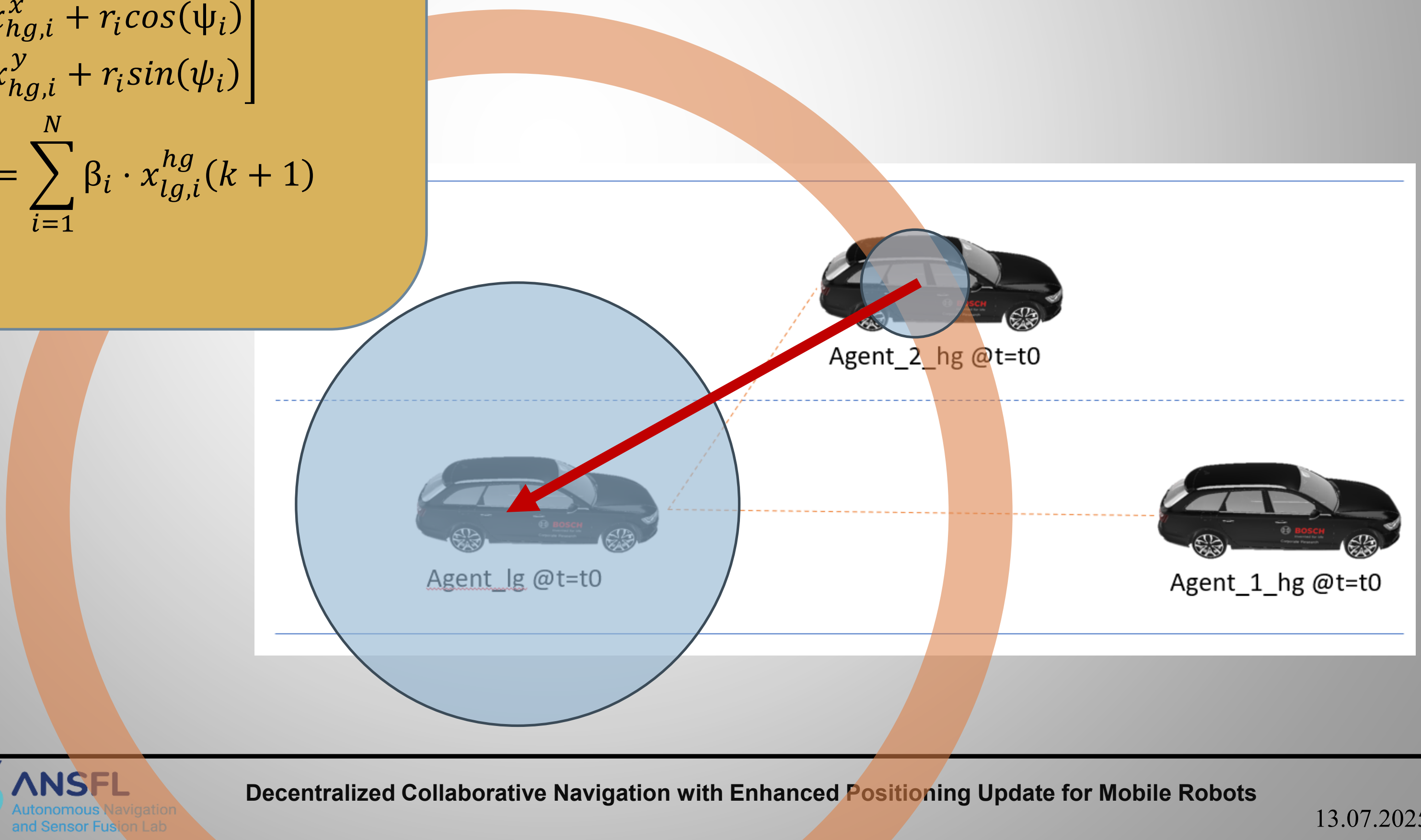


Method: State Projection

$$\psi_i = atan2(x_{hg,i}, x_{lg})$$

$$x_{lg,i}^{hg} = \begin{bmatrix} x_{hg,i}^{x} + r_i cos(\psi_i) \\ x_{hg,i}^{y} + r_i sin(\psi_i) \end{bmatrix}$$

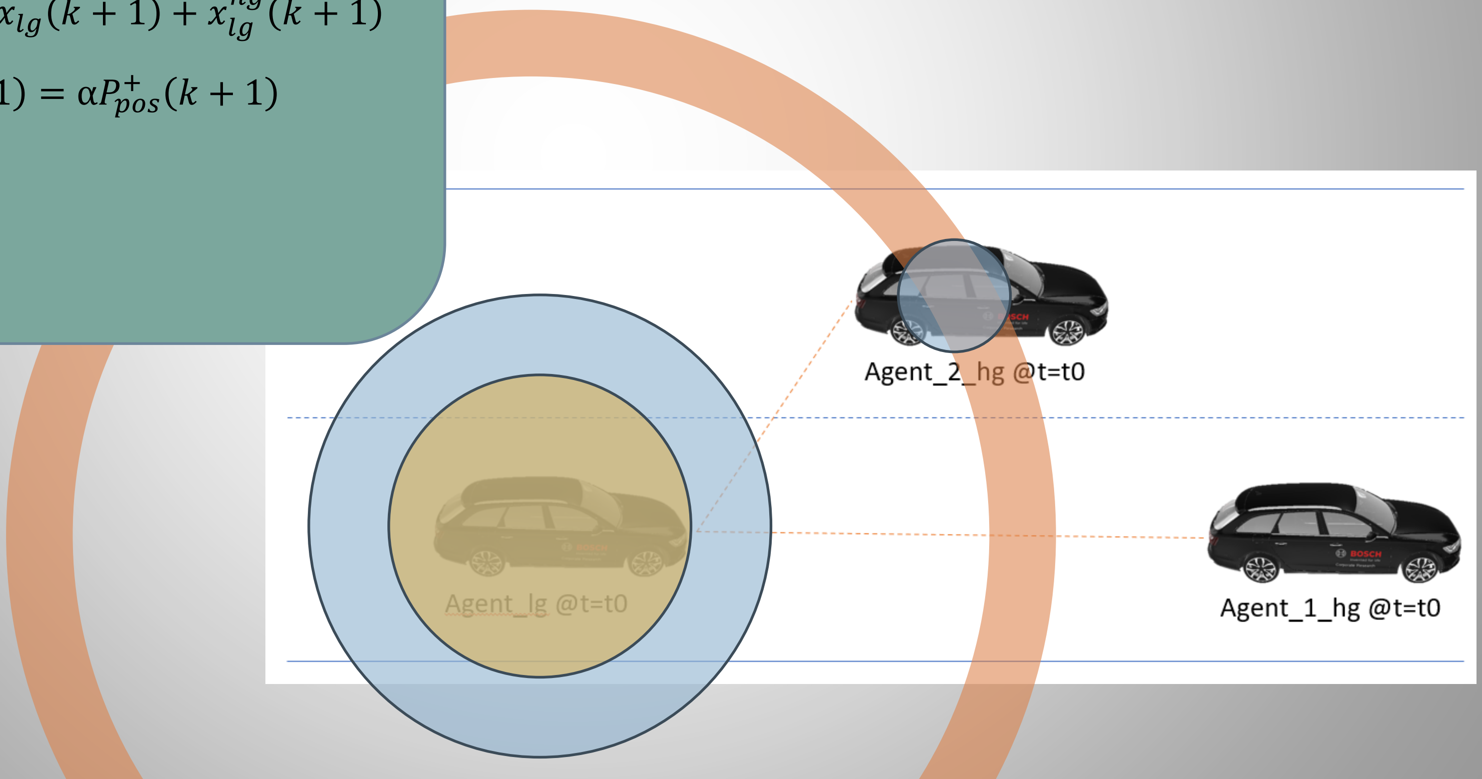
$$x_{lg}^{hg}(k+1) = \sum_{i=1}^{N} \beta_i \cdot x_{lg,i}^{hg}(k+1)$$



Method: EPU Measurement

$$\tilde{x}_{lg}(k+1) = \beta_0 x_{lg}(k+1) + x_{lg}^{hg}(k+1)$$

$$\tilde{P}_{pos}^{+}(k+1) = \alpha P_{pos}^{+}(k+1)$$



Scenarios: Communication Frequency

High communication frequency – make a measurement for each hg-agent's <u>prediction</u> step

t	X	Y	z	range
K+dt_r	28.75	13.45	0.135	2.03
K+2dt_r	29.01	13.32	0.125	2.15
K+3dt_r	29.24	13.19	0.115	2.00
K+4dt_r	29.56	13.02	0.105	2.23
K+1	29.77	12.81	0.096	2.14

Normal communication frequency – make a measurement for each hg-agent's <u>update</u> step

t	X	Y	z	range
K+dt_r	28.75	13.45	0.135	2.03
K+2dt_r	28.75	13.45	0.135	2.15
K+3dt_r	28.75	13.45	0.135	2.00
K+4dt_r	28.75	13.45	0.135	2.23
K+1	29.77	12.81	0.096	2.14

Scenarios: EPU Frequency

High EPU frequency – while using high communication, filter updates every measurement

EPU Update:

$$\tilde{x}_{lg}(k+1) = \beta_0 x_{lg}(k+1) + x_{lg}^{hg}(k+1)$$

$$\tilde{P}_{pos}^{+}(k+1) = \alpha P_{pos}^{+}(k+1)$$

Low EPU frequency – update the filter when hg-agent gets observation

Two ways of operation:

1. Single measurement
2. Batch of measurements

Normal Communication:

$$\psi_i(m) = atan2\left(x_{hg,i}(k), x_{lg}(m)\right)$$

$$x_{lg,i}^{hg}(m) = \begin{bmatrix} x_{hg,i}^{x}(k) + r_i(m)cos(\psi_i(m)) \\ x_{hg,i}^{y}(k) + r_i(m)sin(\psi_i(m)) \end{bmatrix}$$

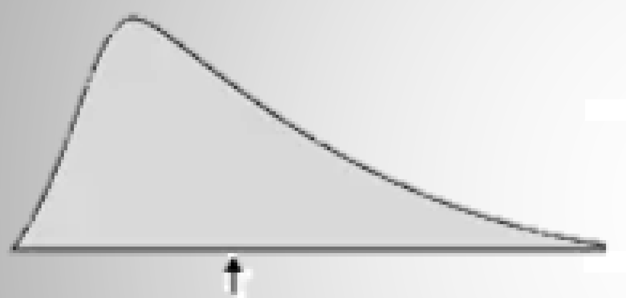
High Communication :

$$\psi_i(m) = atan2\left(x_{hg,i}(m), x_{lg}(m)\right)$$

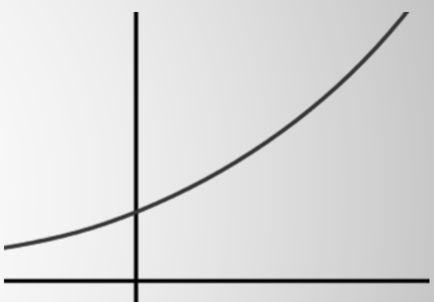
$$x_{lg,i}^{hg}(m) = \begin{bmatrix} x_{hg,i}^{x}(m) + r_i(m)cos(\psi_i(m)) \\ x_{hg,i}^{y}(m) + r_i(m)sin(\psi_i(m)) \end{bmatrix}$$

Scenarios: Weights

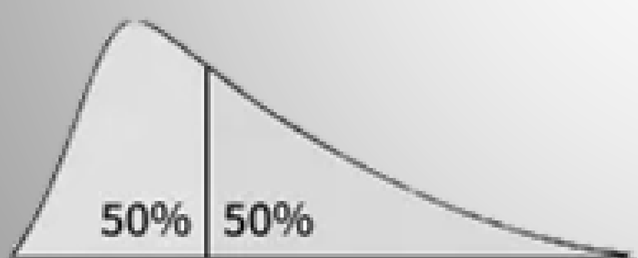
$$X_{lg,i}^{hg}(m) = \left[x_{lg,i}^{hg}(m)\,, m = 0, \dots, M\right]$$
$$x_{lg,i}^{hg}(k+1) = \boldsymbol{w} \cdot X_{lg,i}^{hg}(m)$$



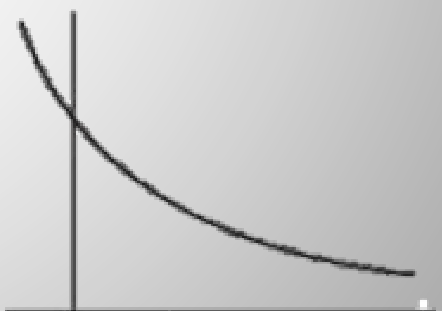
mean



Exp up

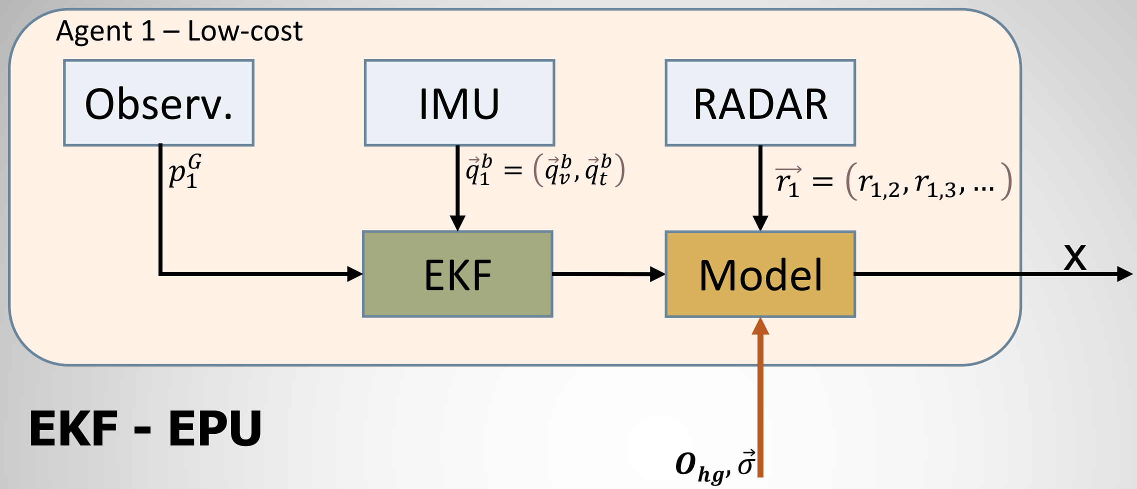


median

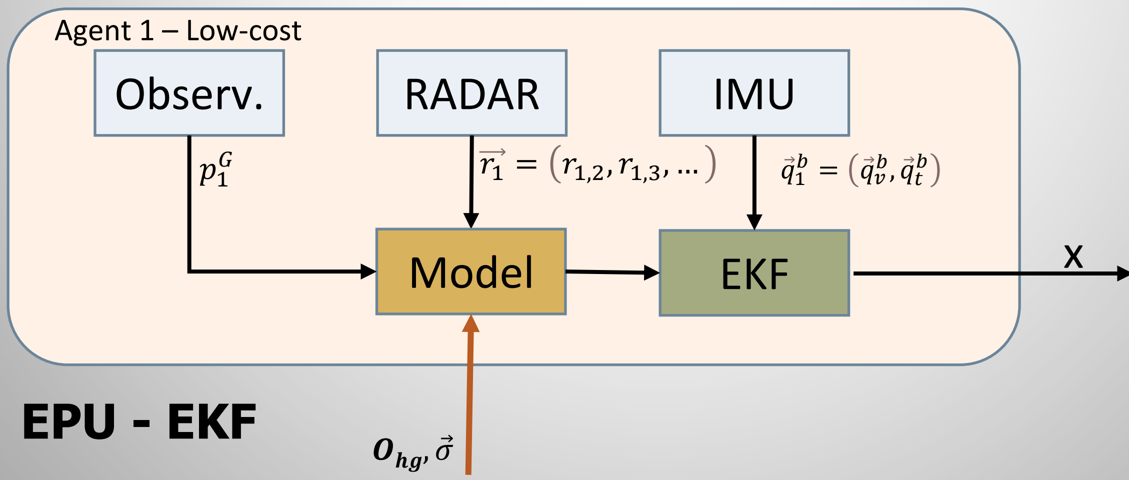


Exp down

Scenarios: Configuration



EKF - EPU



EPU - EKF

Scenarios: Summary

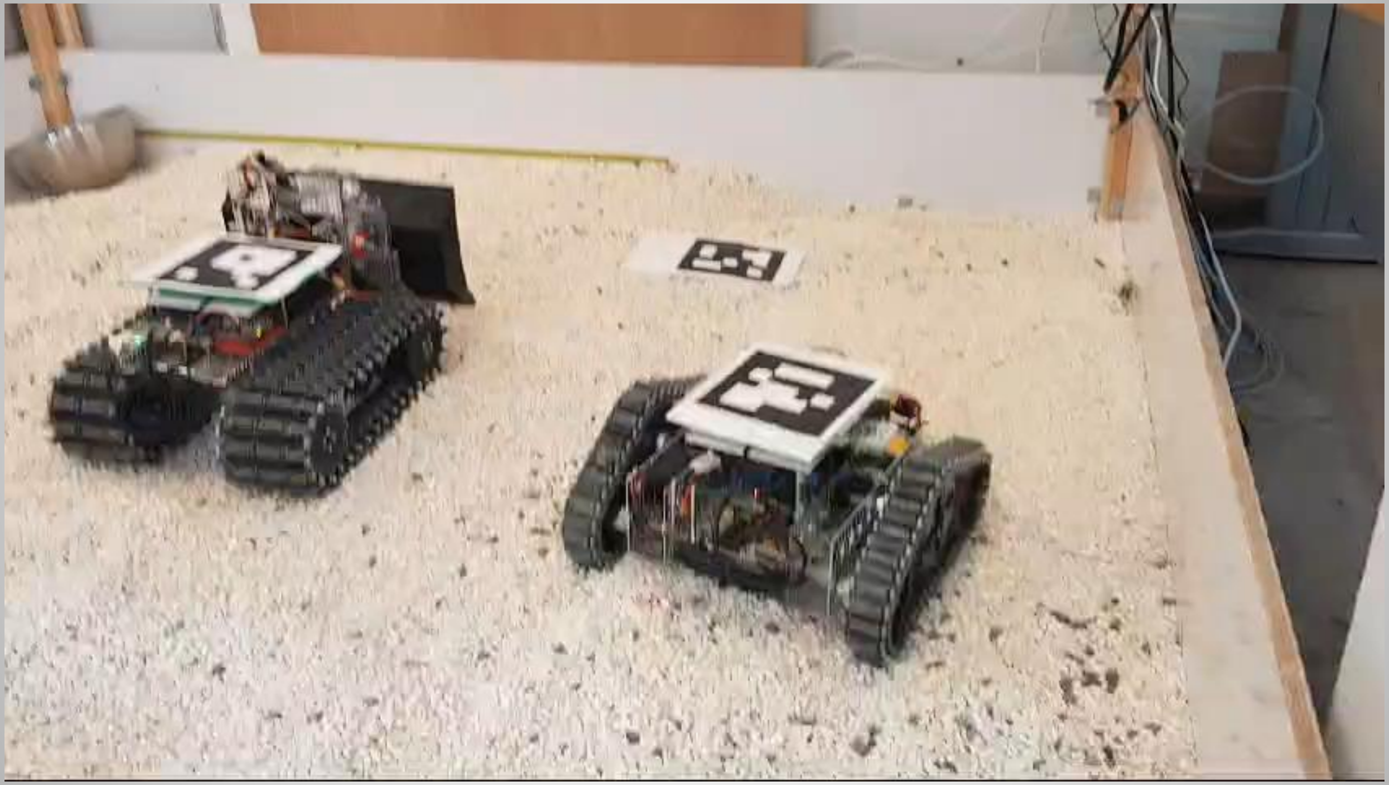
Different scenarios examined for EKF-EPU approach.

Scenario	Information Sharing	EPU Frequency	Comm Frequency	Weighted Averaging Vector
1 (baseline)	No	No	No	No
2	Yes	Low	No	No
3	Yes	Low	High	Mean
4	Yes	Low	High	Median
5	Yes	Low	High	Exp up
6	Yes	Low	High	Exp down
7	Yes	High	Normal	No
8	Yes	Low	Normal	Mean
9	Yes	Low	Normal	Median
10	Yes	Low	Normal	Exp up
11	Yes	Low	Normal	Exp down
12	Yes	High	High	No

Different scenarios examined for EPU-EKF approach.

Scenario	Informatio n Sharing	EPU Frequency	EKF Frequency	Weighted Averaging Vector
1 (baseline)	No	No	Low	No
13	Yes	Low	Low	No
14	Yes	Low	Low	Mean
15	Yes	Low	Low	Median
16	Yes	Low	Low	Exp up
17	Yes	Low	Low	Exp down
18	Yes	High	High	No

Results:



Results: Simulation

Simulation RMSE [m] results for EPU-EKF Scenarios over a one-minute trajectory.

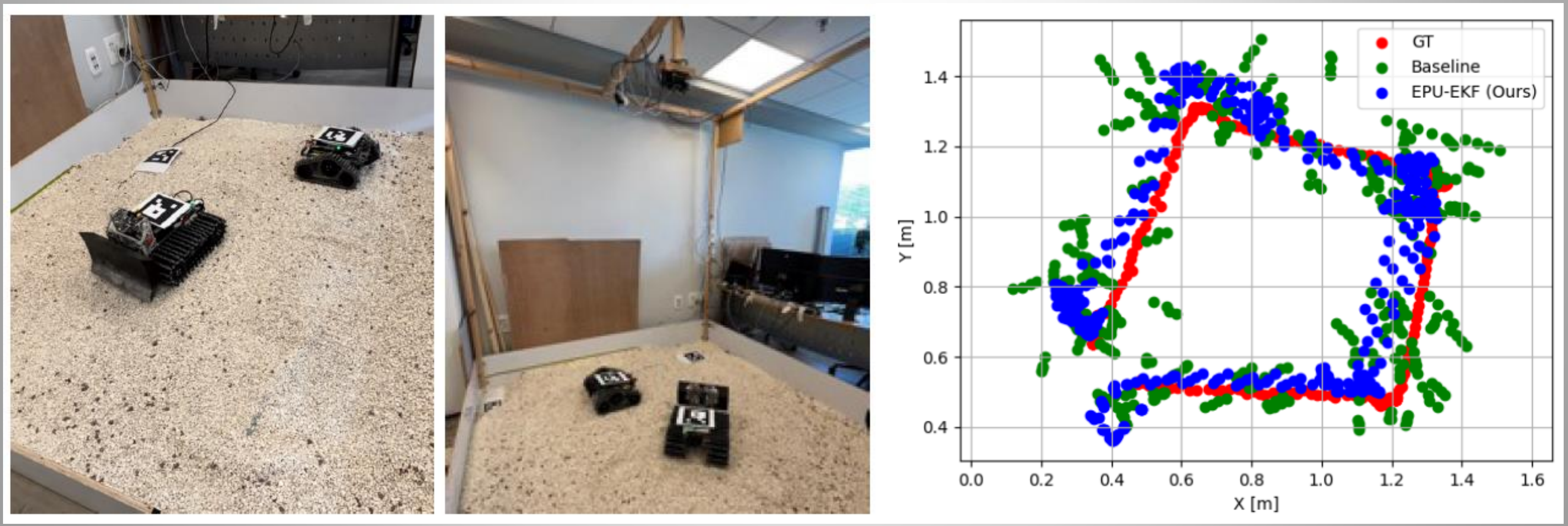
Scenario	Range measurement Noise: Low	Range measurement Noise: High
1	6.13	6.13
13	6.17	7.05
14	**1.66**	2.71
15	5.65	10.23
16	1.76	**2.6**
17	1.78	3.13
18	5.31	6.54

[14] Low EPU frequency with high communication using HF-to-LF with mean
[16] Low EPU frequency with high communication using HF-to-LF with exp up

Results: Experiments

RMSE [m] of the baseline and the EPU-EKF approach on a real robotic environment.

Scenario	Range measurement Noise: Low	Range measurement Noise: High
1 (baseline)	6.02	6.02
14 (ours)	**2.04**	2.14



Thank You!

Happy to take questions

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