Cooperative Localization Algorithms for Improved Road Navigation

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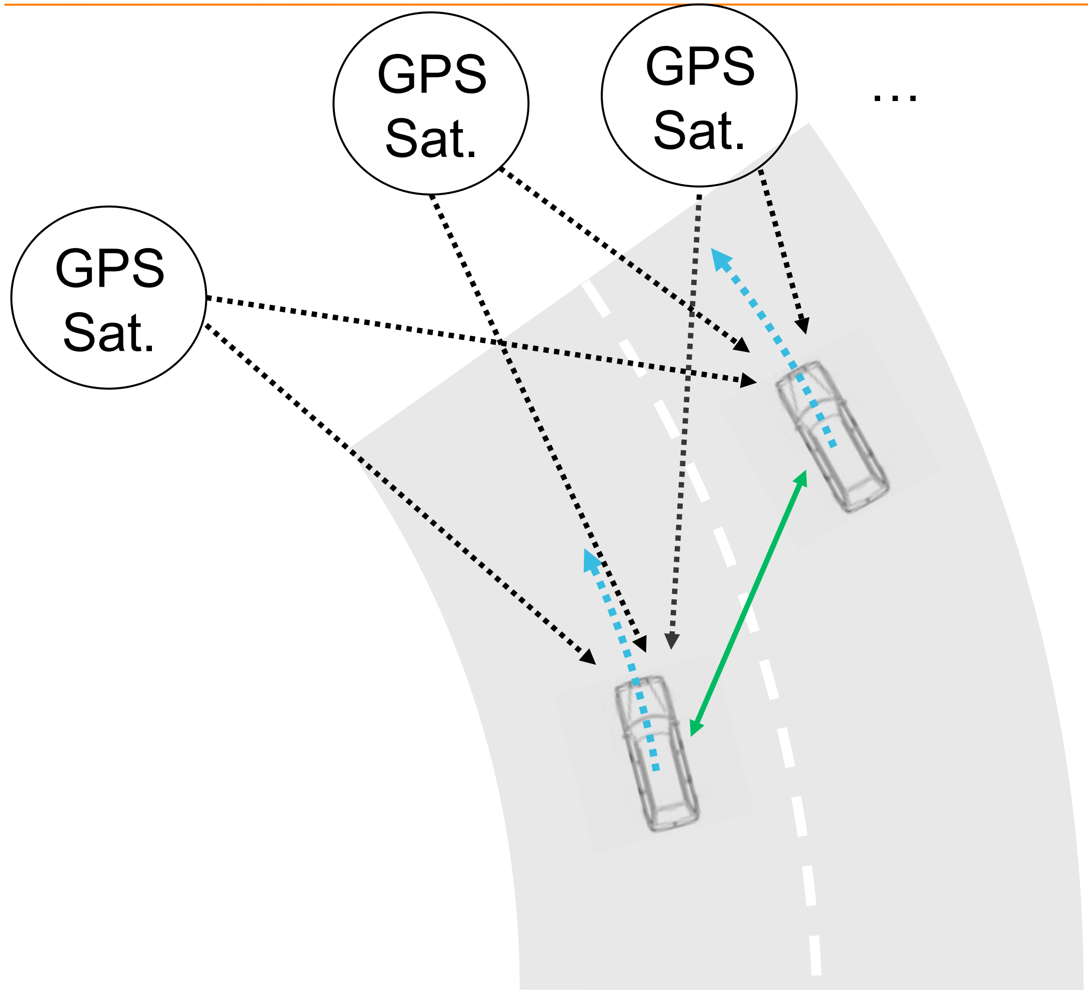
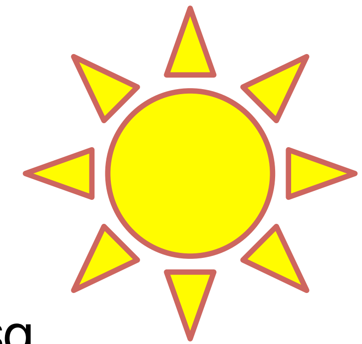
Cooperative Localization - Introduction



- Using smoothed pseudo range double differences or other sensors like radar or laser
- Intended to be used in automotive field (but not limited to it)
- e.g. helps for lane precise localization

Distributed Data Fusion - Example





$$X = (R) = \{r; s\}$$

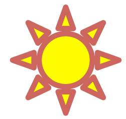

$$P(Z = r|X = r) = 0.8$$
$$P(Z = r|X = s) = 0.4$$

$$P(Z = s|X = r) = 0.4$$
$$P(Z = r|X = s) = 0.3$$

Distributed Data Fusion - Example

$P(X = r|Z_1 = r) = 0.8$ ⟶ $P(X = r|Z_1 = r) = 0.8$

$$P(X = r|Z_1 = r \cup Z_2 = s) = \frac{0.4 \cdot 0.8}{0.4 \cdot 0.8 + 0.7 \cdot 0.2} \approx 0.7$$



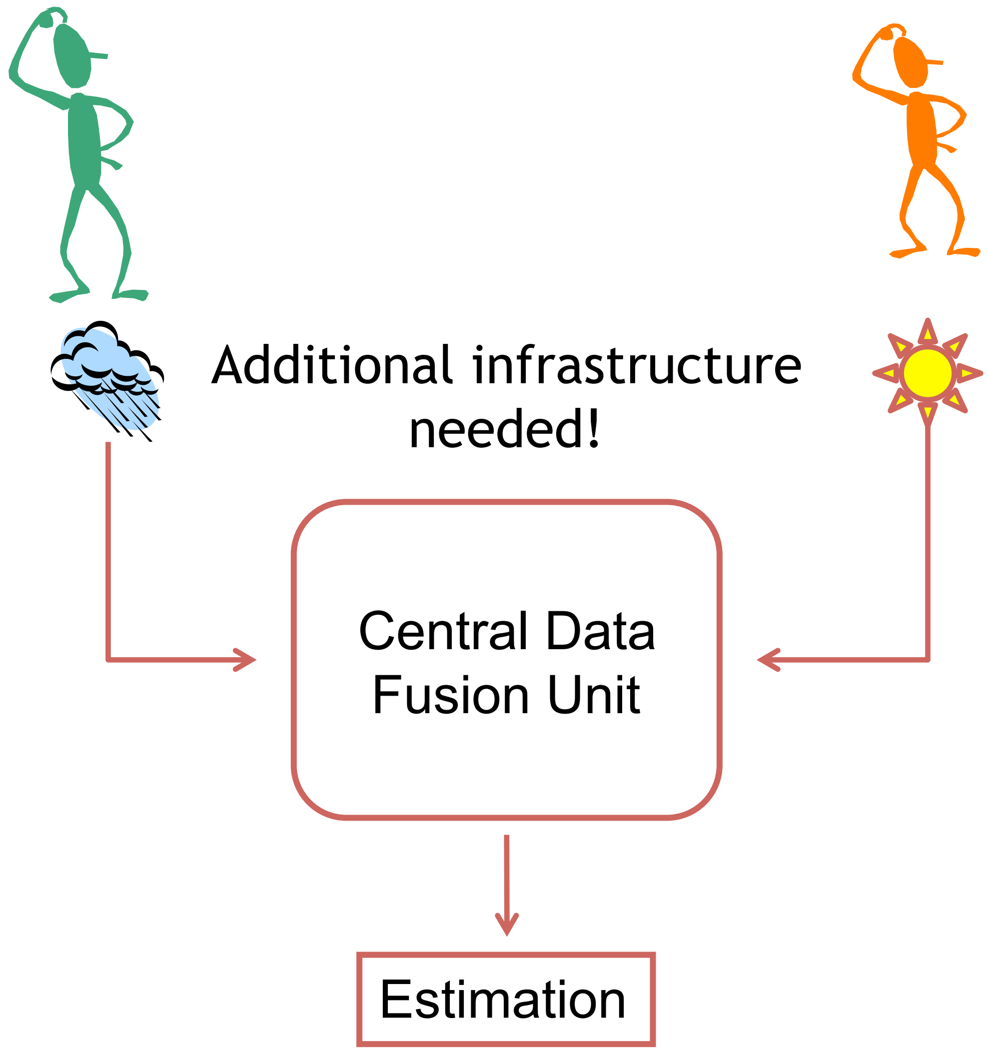
$P(X = r|Z_1 \cup Z_2) = \frac{0.7 \cdot 0.8}{0.7 \cdot 0.8 + 0.3 \cdot 0.2} \approx 0.9$ ⟵ ! ⟵ $P(X = r|Z_1 \cup Z_2) \approx 0.7$

$P(X = r|Z_1 \cup Z_2) \approx 0.9$ ⟶ ! ⟶ ...

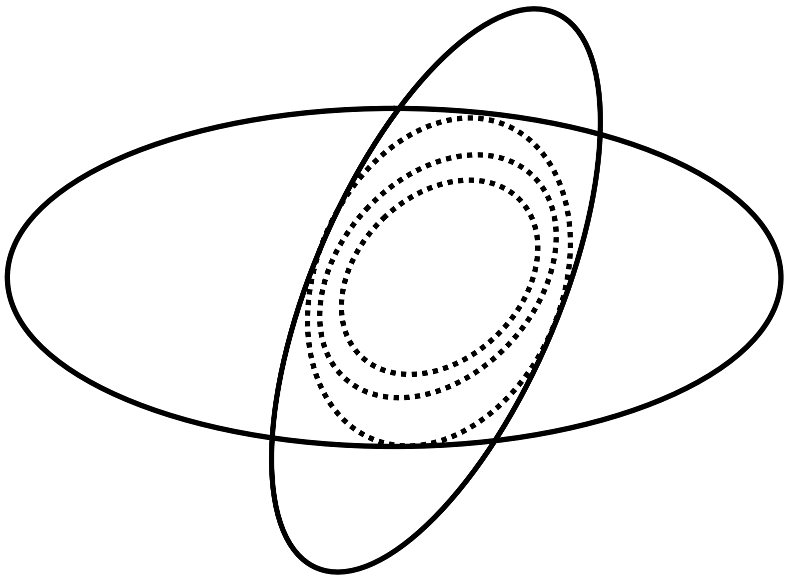
$\vdots$!

$$P(X = r|Z_1 \cup Z_2) \to 1$$

Centralized Data Fusion – One way out



Distributed Data Fusion – Covariance Intersection



$$P_{cc}^{-1} = \omega P_{aa}^{-1} + (1-\omega) P_{bb}^{-1} \qquad \omega \in [0,1]$$

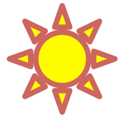
$$P_{cc}^{-1} c = \omega P_{aa}^{-1} a + (1-\omega) P_{bb}^{-1} b$$

Distributed Data Fusion - Example

$P(X = r | Z_1 = r) = 0.8$ $\longrightarrow$ $P(X = r | Z_1 = r) = 0.8$

Common Information

$P(X = r | Z_1 = r \cup Z_2 = s) = \frac{0.4 \cdot 0.8}{0.4 \cdot 0.8 + 0.7 \cdot 0.2} \approx 0.7$



$P_{new}(X = r) \approx 0.37$ $P_{new} = \propto \frac{P(X | Z_1 \cup Z_2)}{P(X | Z_1)}$ $\longleftarrow$ $P(X = r | Z_1 \cup Z_2) \approx 0.7$

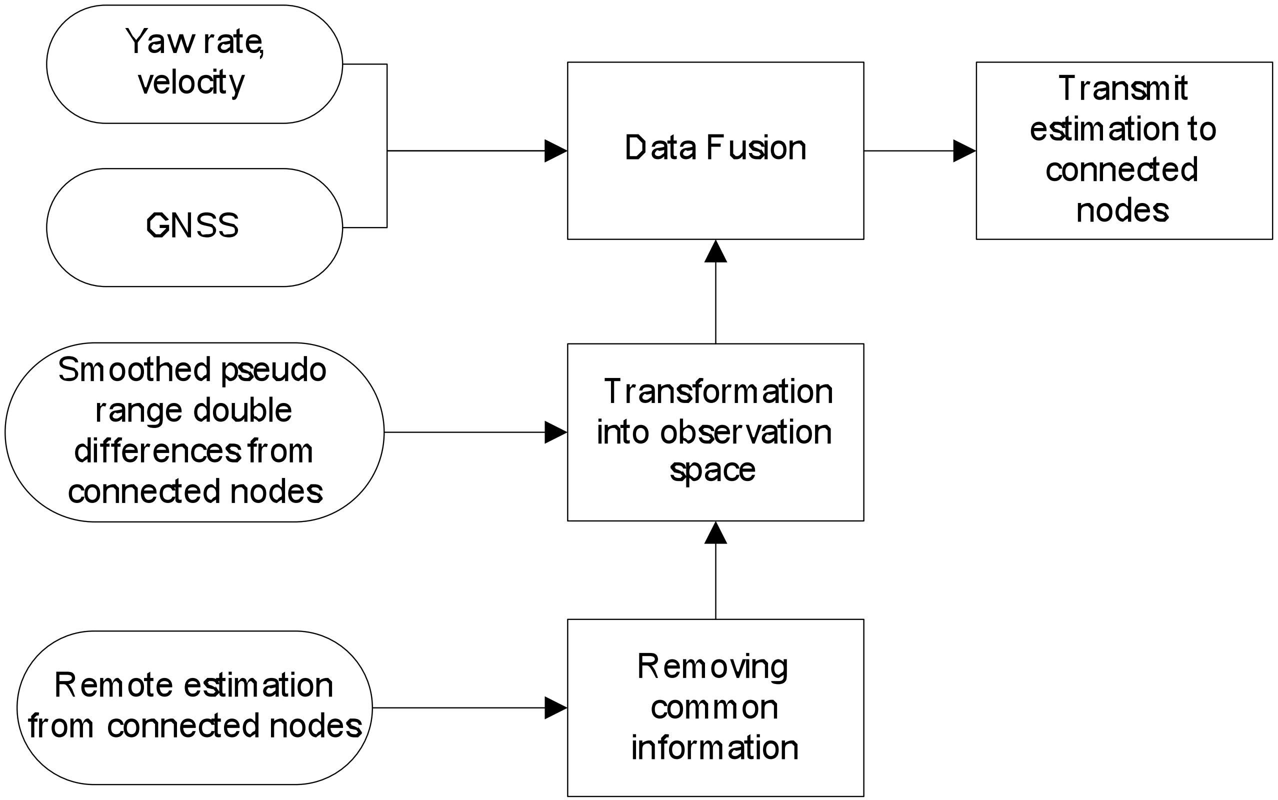
$P(X = r | Z_1 \cup Z_2) \approx 0.7$

Distributed Data Fusion – Removing Common Information

- Data fusion of remote and local information considering common information

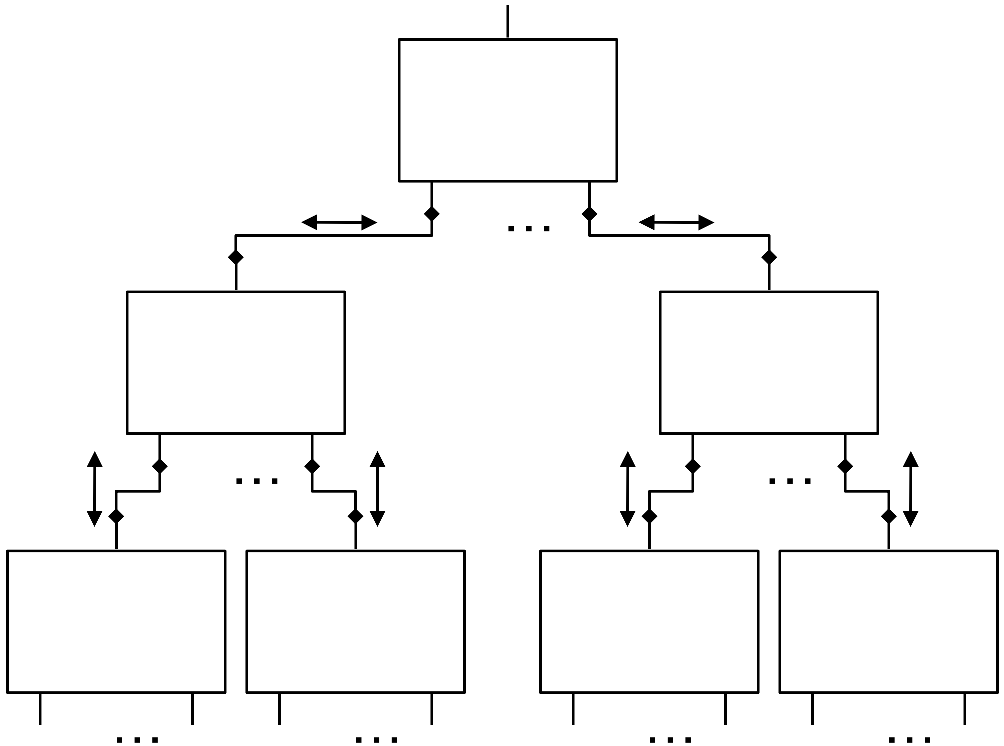
$$p(x|Z_l \cup Z_r) \propto \frac{\overbrace{p(x|Z_l)}^{\text{local}}\,\overbrace{p(x|Z_r)}^{\text{remote}}}{\underbrace{p(x|Z_l \cap Z_r)}_{\text{common}}}$$

Cooperative Localization – The System



Cooperative Localization –Network Topology

Tree structured network architecture tracks the common information between two nodes



Cooperative Localization – Estimated State

- State space consists of the vehicle's position and heading

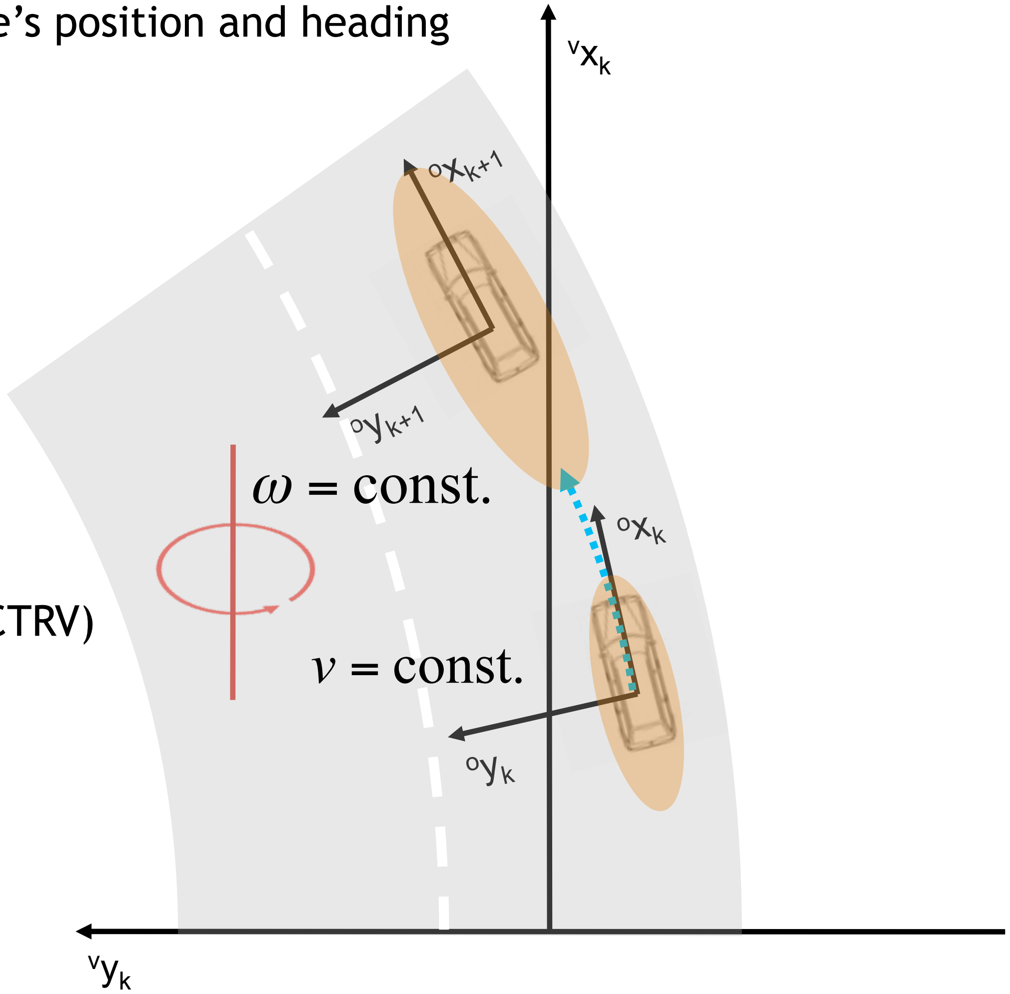
$$\underline{x} = \left[\, x \quad y \quad \mu \,\right]^T$$

- non-linear state transition

$$\underline{x}(t+T) = f\left(\underline{x}(t); \underline{u}(t)\right)$$

$$\underline{u}(t) = \left(\, v \quad \omega \,\right)^T$$

- Movement model
  Constant Turn Rate & Velocity (CTRV)

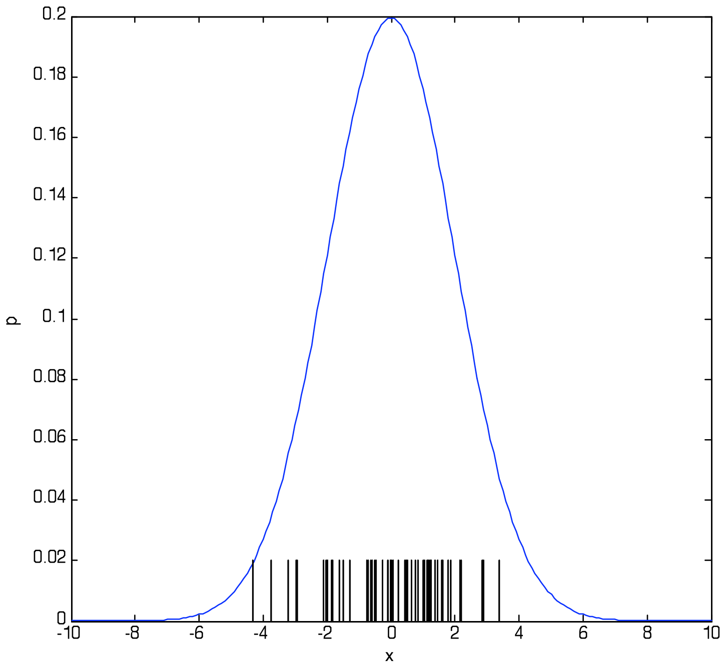


Cooperative Localization – Filter Technology

- Particle filter represent an arbitrary PDF by samples drawn from it

$$S_k = \left\{ \left(x_k^{(i)}; \omega_k^{(i)} \right) \middle| i = 1, \ldots, N_p \right\}$$

$$p(X_k | Z_k) \approx \sum_{i=1}^{N_p} \omega_k^{(i)} \delta(X_k - X_k^{(i)})$$



Cooperative Localization – Filter Technology

- judging particles on the measurement likelihood function

$$\omega_k^{(i)} = w_{k-1}^{(i)} \frac{p(z_k|x_k^{(i)})\,p(x_k^{(i)}|x_{k-1}^{(i)})}{q(x_k^{(i)}|x_{k-1}^{(i)}, z_k)}$$

- Kullback-Leibler divergence is used for resampling

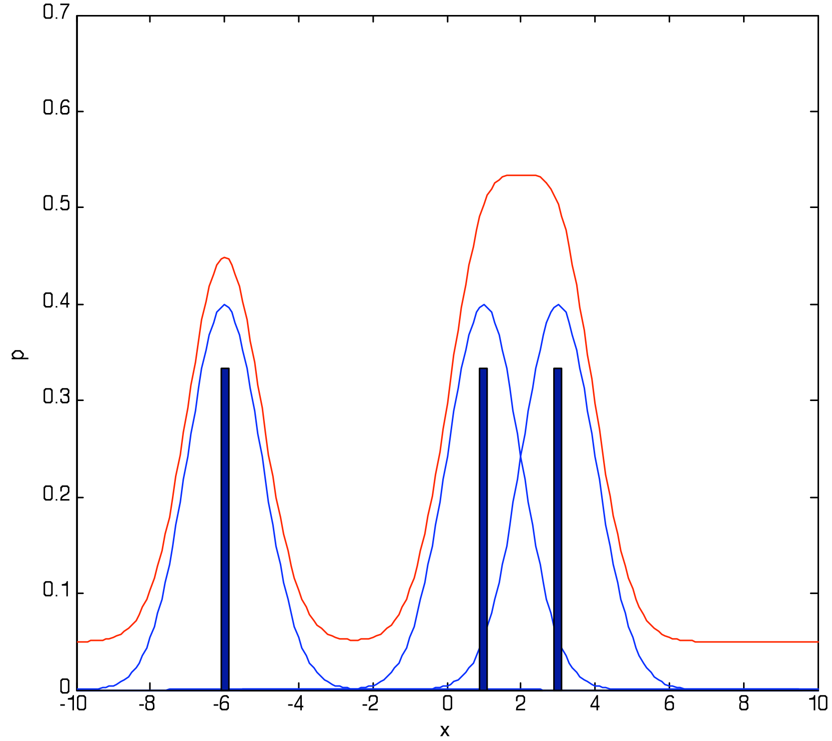
$$K(p, q) = \sum_x p(x) \log \frac{p(x)}{q(x)}$$

  - keeps bandwidth low as the number of particles is adaptive to the current estimation

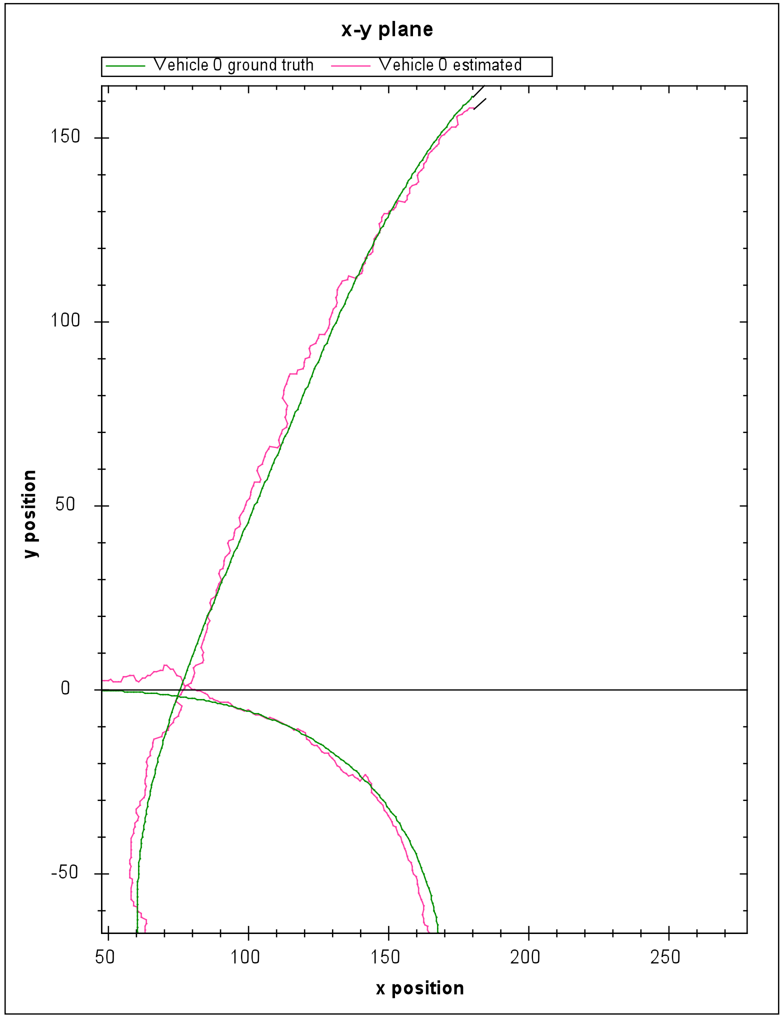
Cooperative Localization – Common Information and PF

- Transformation of received distribution into local state space:
  Shifting the received distribution by
  the smoothed pseudo range double difference distribution

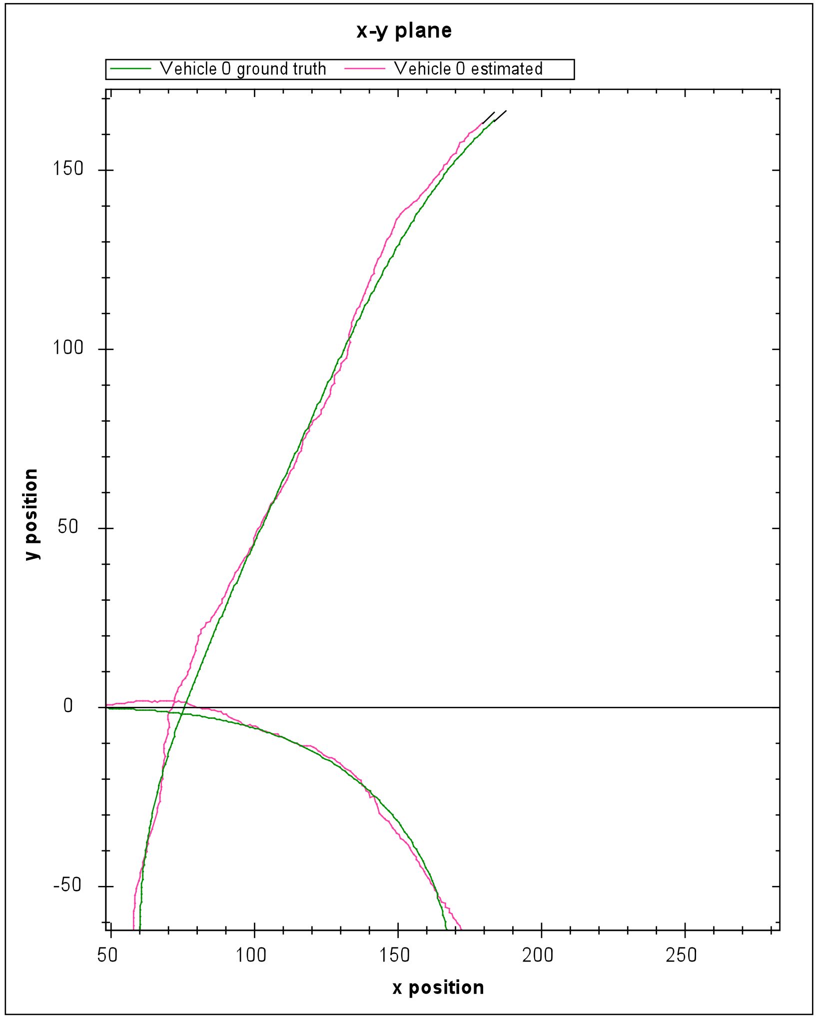
- Converting one distribution into continuous
  representation for support equality



Cooperative Localization – Simulation Results



Without communication



With communication

Cooperative Localization – Simulation Results

RMSE for different number of communicating vehicles after 300 samples

number of vehicles	1	2		3			4			
vehilce v_i	0	0	1	0	1	2	0	1	2	3
error e	4.1	3.5	2.8	3.3	2.6	2.4	3.2	2.6	2.4	2.5
mean error $\bar{e}$	4.1	3.15		2.76			2.67			

Conclusion

- Decentralized networks provide a scalable way of fusing information produced by moving groups of vehicles
- Improved position estimates
- Avoiding data incest by removing common information using a general method
- Extendable by arbitrary sensors and further a priori knowledge (like maps) by using particle representations
- Future work: Evaluation the proposed system with real data

Thank you

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