COOPERATIVE VEHICULAR LOCALIZATION: RECENT PROGRESSES AND CHALLENGES

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Observatoire de Paris, Meudon - March 29th 2018

OUTLINE

- Context and Motivations
- V2V Cooperative Localization
- Hybrid V2V Cooperative Localization
- Hybrid V2X Multisensor Cooperative Localization
- Conclusions and Perspectives

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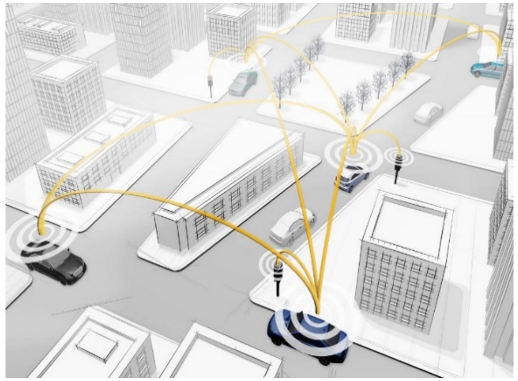
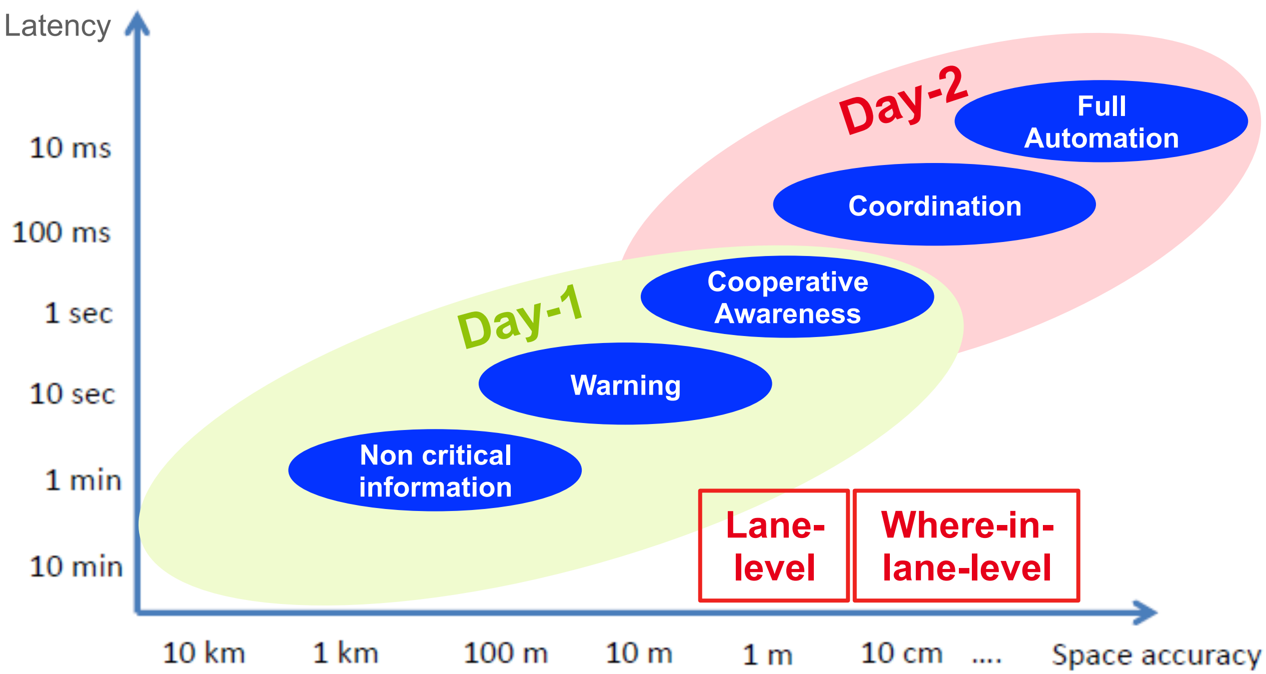
COOPERATIVE – INTELLIGENT TRANSPORT SYSTEMS (C-ITS)

- **Wireless communication between vehicles (V2V) and roadside infrastructure (V2I) → V2X**
  - Road traffic safety
  - Road traffic efficiency



Source: Daimler

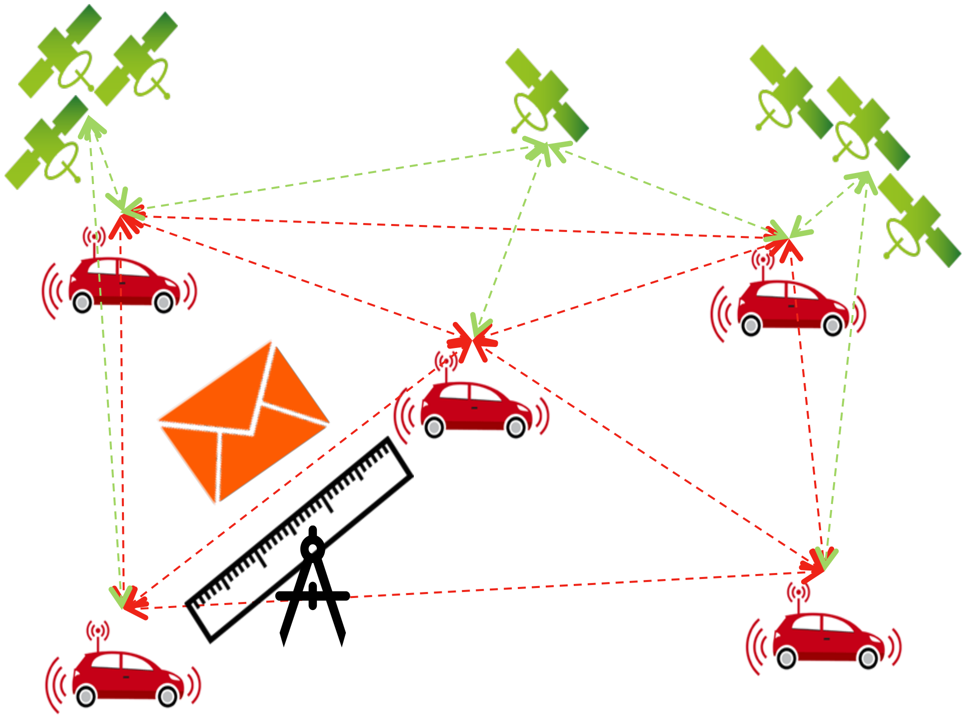
- **C-ITS applications road map (C2C-CC): Day-1 & Day-2**



High accuracy absolute localization is needed, regardless of **operating conditions**

COOPERATIVE LOCALIZATION BASICS

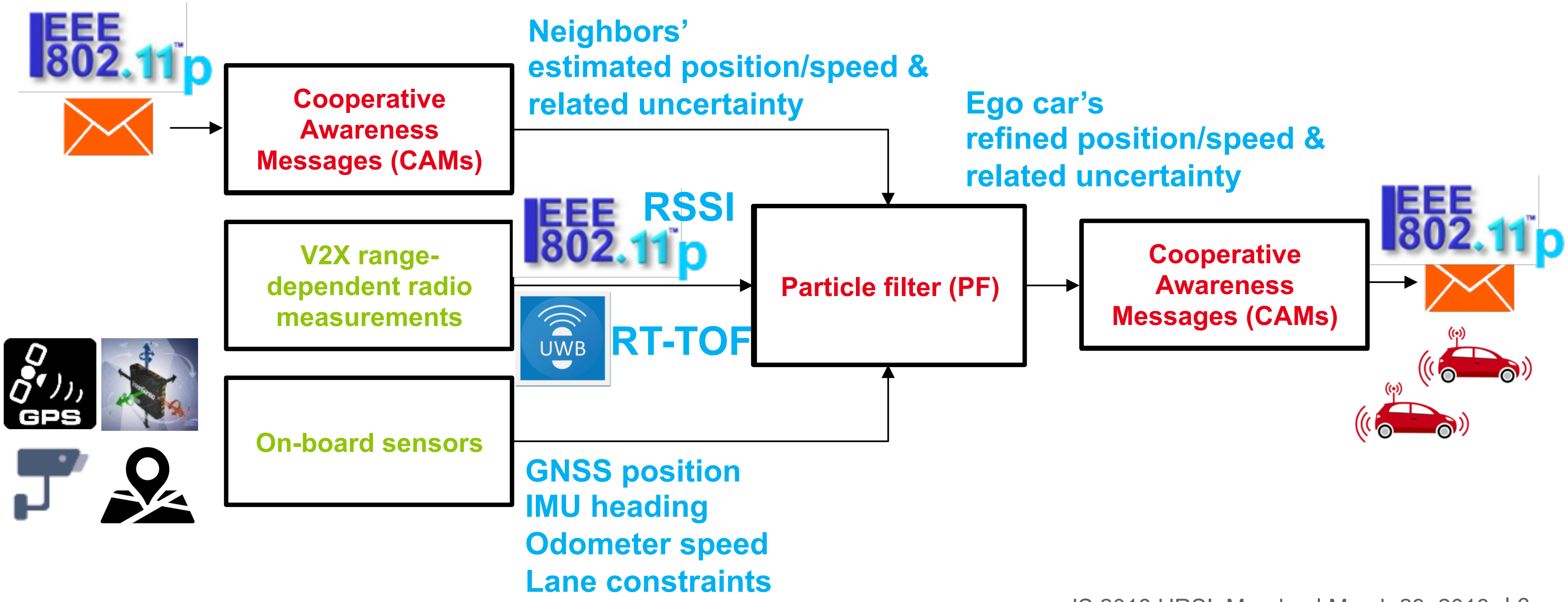
- **Expected benefits**
  - Neighbors (hopefully well positioned) → "Virtual anchors"
  - Diversity, redundancy, geometric ambiguity solving → Better accuracy/ resilience



  - Methods mostly validated under moderate mobility so far (e.g., WSN)
    → Open/unprecedented challenges in the vehicular context

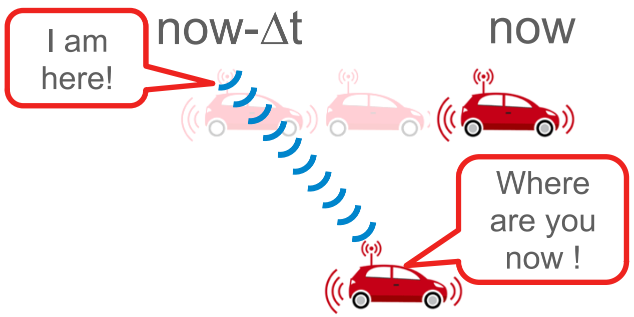
CONSIDERED TECHNOLOGIES

Maturity	Technology	Frequency	Metric
Today	**ITS-G5 / 802.11p**	**5.9 GHz**	**RSSI**
Today	**IR-UWB / 802.15.4a**	**~ 4 GHz**	**TOA / RT-TOF**
Prospective	4G LTE V2X	2 GHz	Under specification
Prospective	5G mmWave V2X	30 – 100 GHz	AOA / AOD / TOA
Prospective	WiFi extension	2.4 GHz	Not standardized

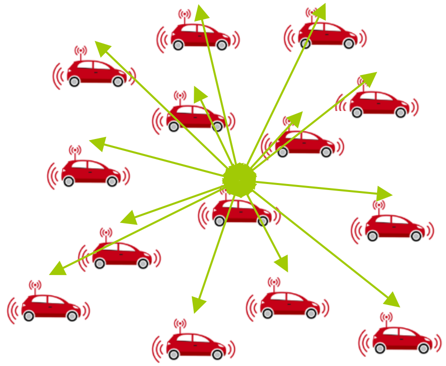


CHALLENGES & OPEN RESEARCH QUESTIONS

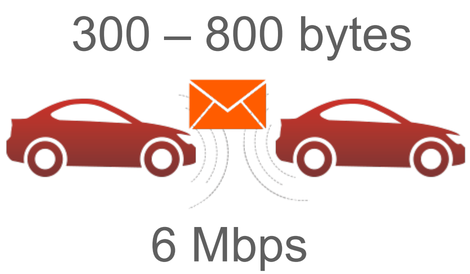
Highly dynamic mobility



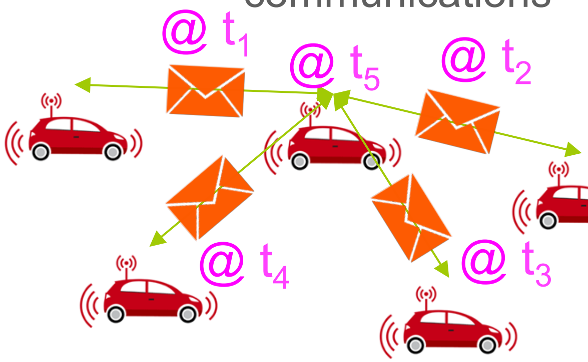
Large amount of vehicles



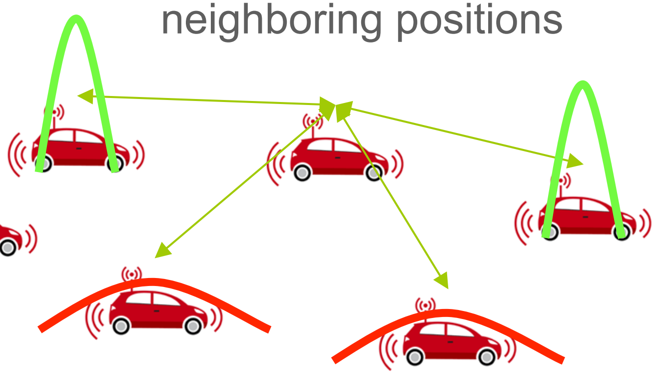
Limited V2X communication channel



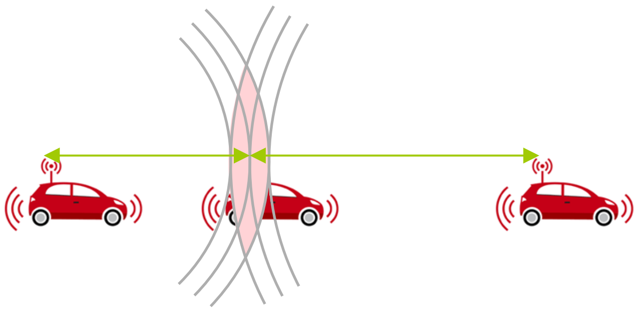
Unscheduled V2X communications



Imperfect/unfavorable neighboring positions



Unplanned geometry



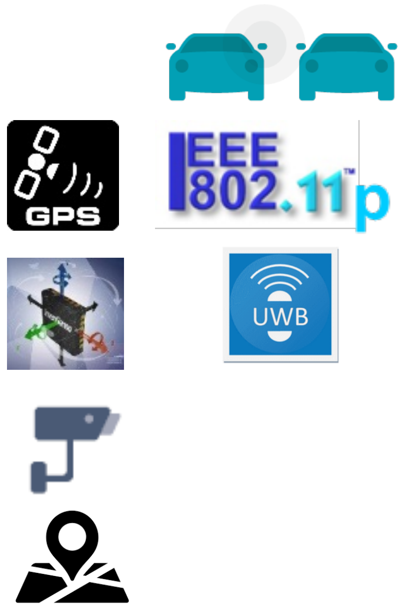
Can sub-meter localization accuracy be already met through low-complexity CLoc strategies between connected vehicles with standard technologies?

GRADUAL ASSESSMENT APPROACH

V2V CLoc

Hybrid V2V CLoc

Hybrid V2V & Multisensor CLoc



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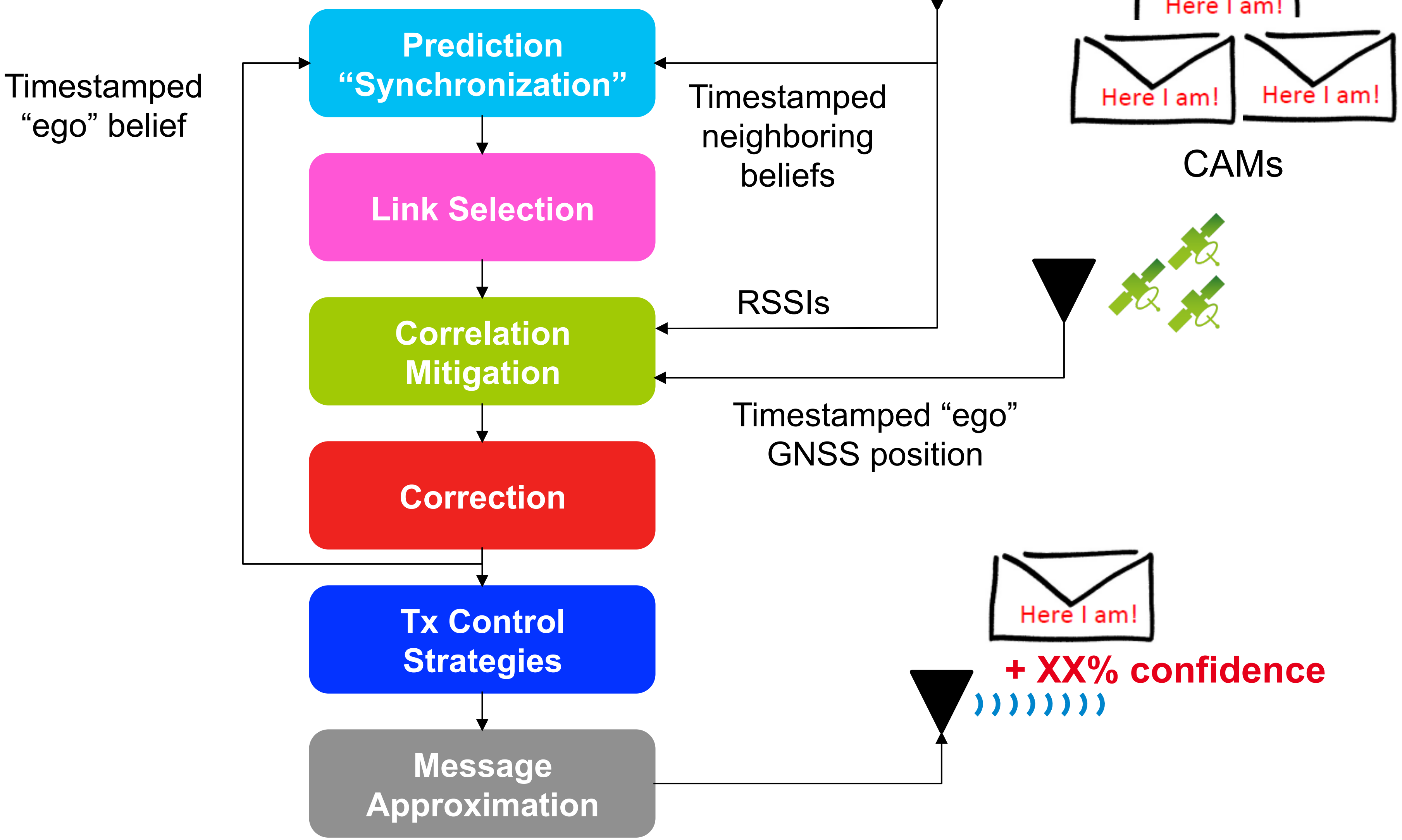
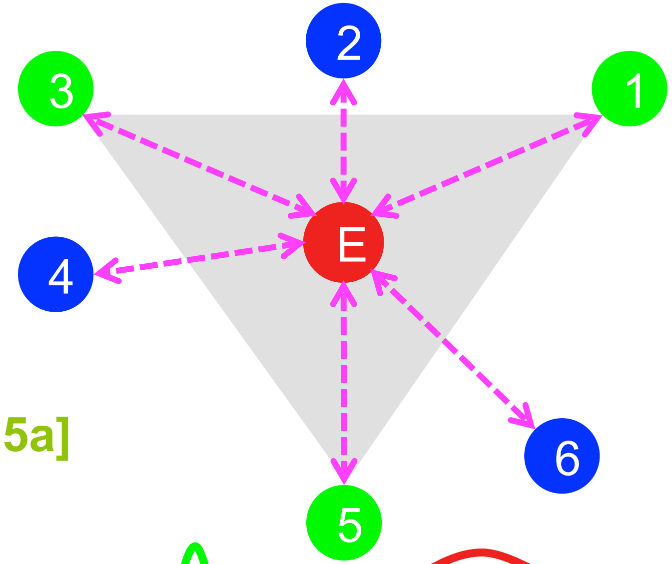
NOMINAL COOPERATIVE FRAMEWORK

- At each “ego” vehicle…

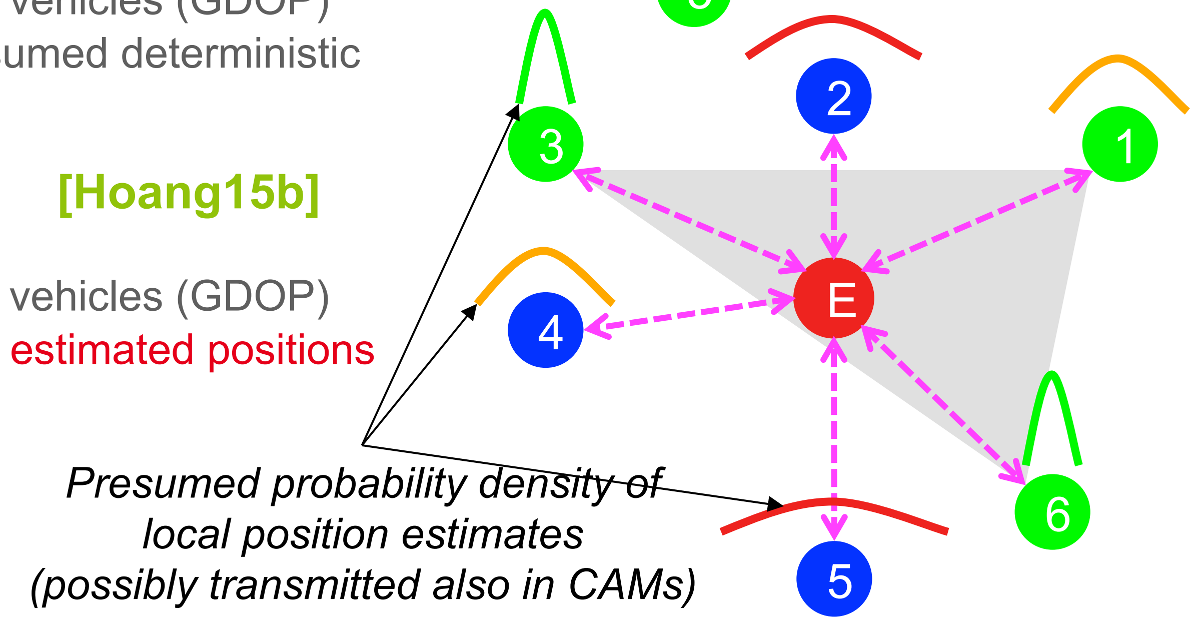


LINKS SELECTION
NON-BAYESIAN VS. BAYESIAN CRITERIA

- **Link selection based on theoretical positioning performance bounds (CRLB) conditioned on a priori sub-constellations**

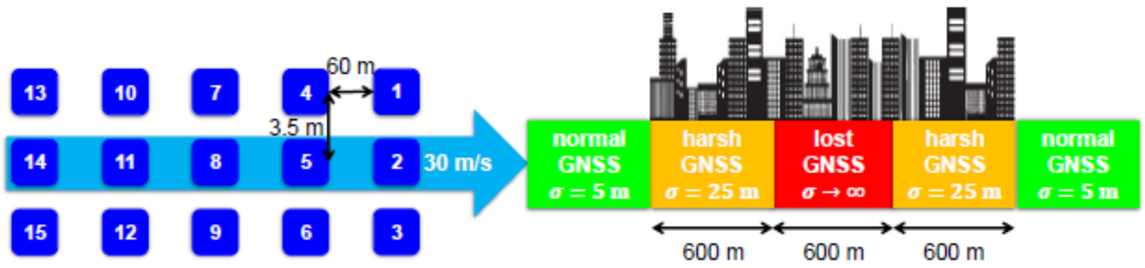


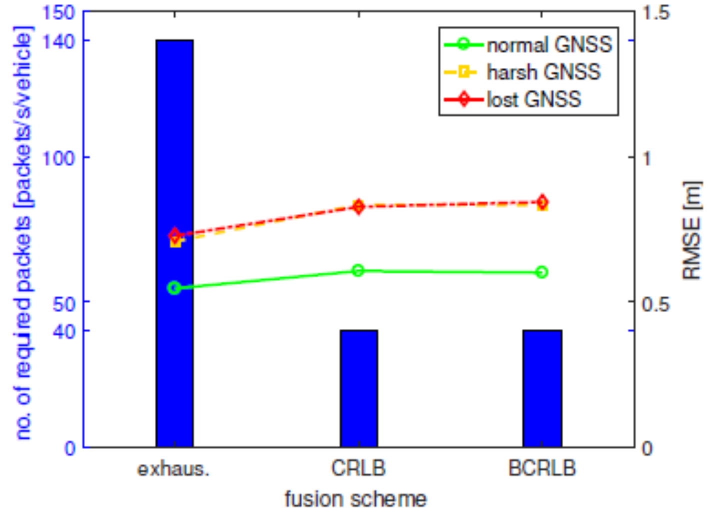
- Non-Bayesian CRLB criterion **[Hoang15a]**
  - Radio link quality
  - Geometry of neighboring vehicles (GDOP)
  - All involved positions assumed deterministic (& perfect)
- Bayesian CRLB criterion **[Hoang15b]**
  - Radio link quality
  - Geometry of neighboring vehicles (GDOP)
  - Uncertainty of neighbors' estimated positions



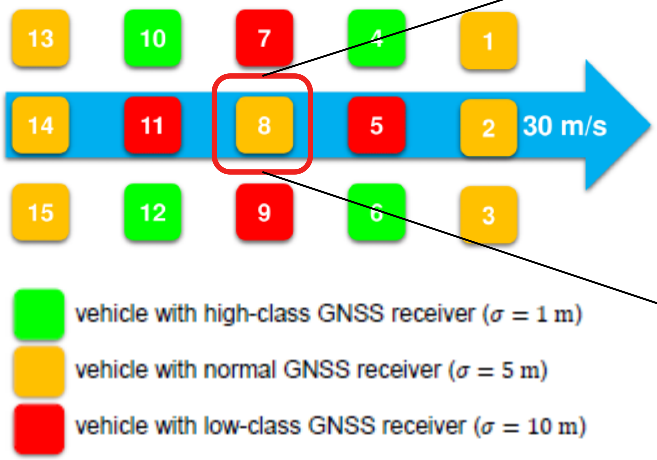
LINKS SELECTION
PERFORMANCE EVALUATION

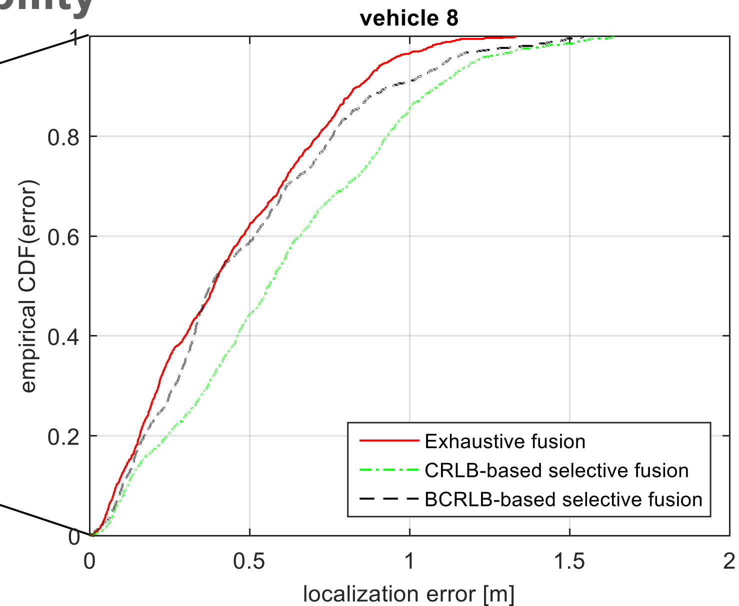
- **Large-scale GNSS error (urban canyon)**
  - Saved complexity at (almost) no accuracy degradation (vs. exhaustive cooperation)





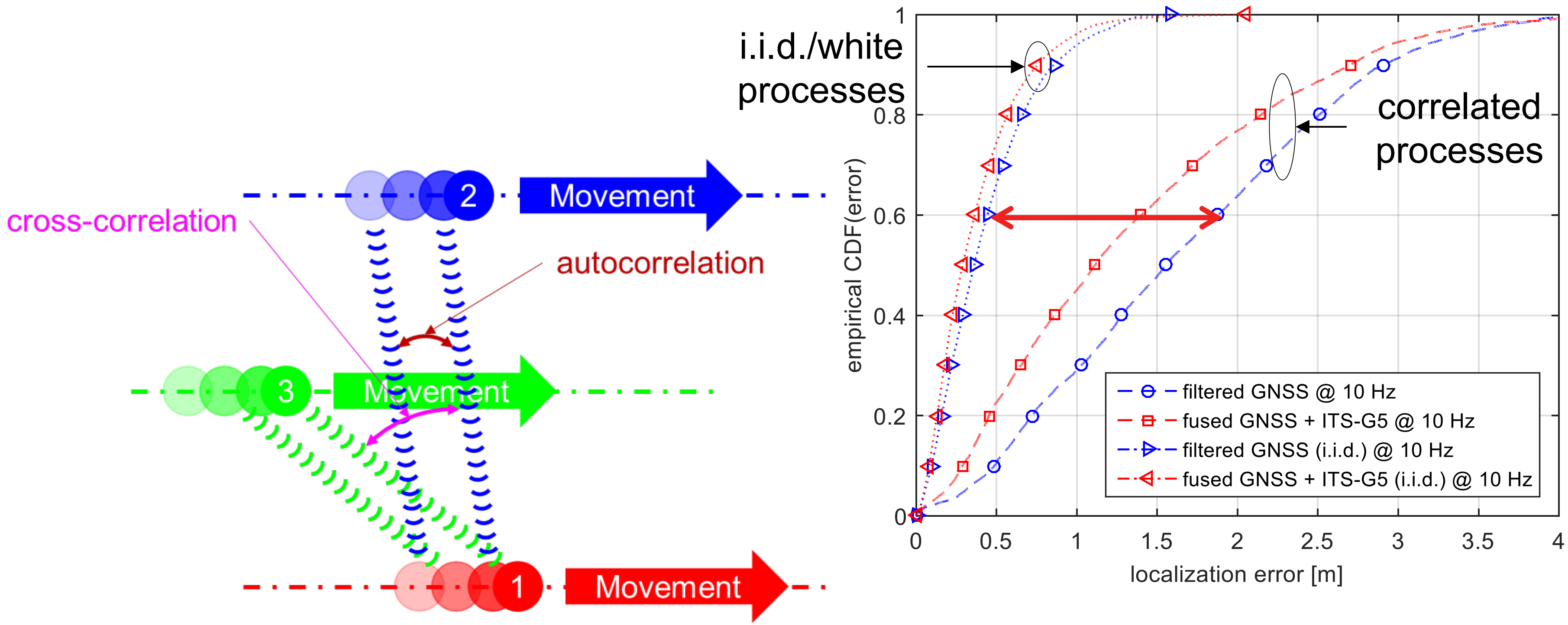
- **Small-scale locally degraded GNSS capability**
  - Local accuracy gains with Bayesian-CRLB criterion (vs. non-Bayesian)





IMPACT OF SPACE-TIME MEASUREMENT NOISE CORRELATIONS

- **Why is correlation a threat ?**
  - Inherent/specific to constrained vehicular mobility under typical refresh rates
  - Cannot properly filter out error processes (assumed white)
  - Misses hidden/fruitful location info
  - Causes filter over-confidence (in inaccurate estimates)

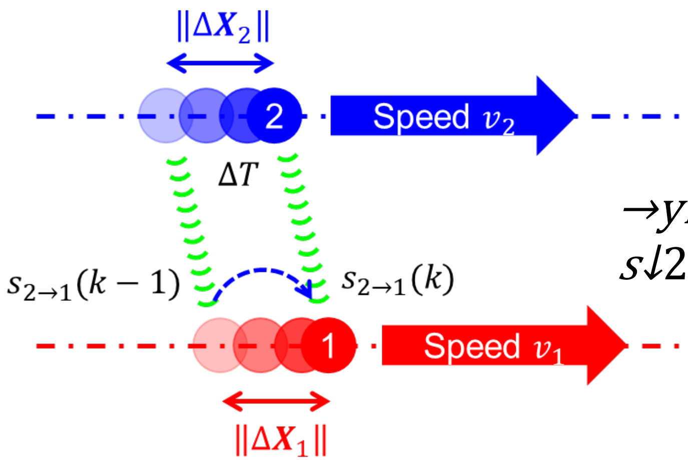


MITIGATION OF SPACE-TIME CORRELATIONS

- **Signal level mitigation**
  - Empirical cross-measurement correlations
    → Compensate for info loss

$$r_{cross}^{Sh}(2\to1,3\to1)=\exp\left(-\|\boldsymbol{X}_3-\boldsymbol{X}_2\|+\Delta\boldsymbol{X}_1/d_{cor}^{Sh}\log 2\right)$$

  - Differential measurements
    → Eliminate the correlated part (back to i.i.d./white assumptions)



$$r_{auto}^{Sh}(2\to1)=\exp\left(-\|\Delta\boldsymbol{X}_2\|+\|\Delta\boldsymbol{X}_1\|/d_{cor}^{Sh}\log 2\right)$$

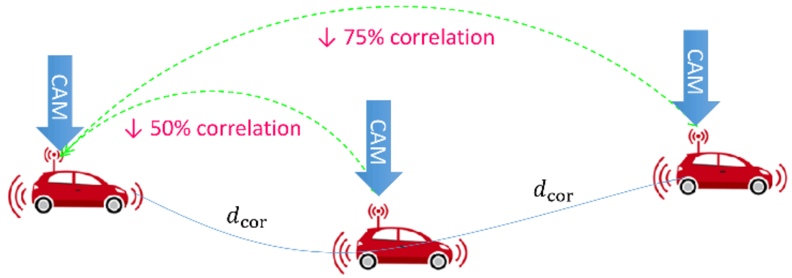
$$\xrightarrow{yields} s_{2\to1}(k)=\lambda^{Sh}s_{2\to1}(k-1)+s_{2\to1}'(k)$$

[Hoang16b]

correlated — white

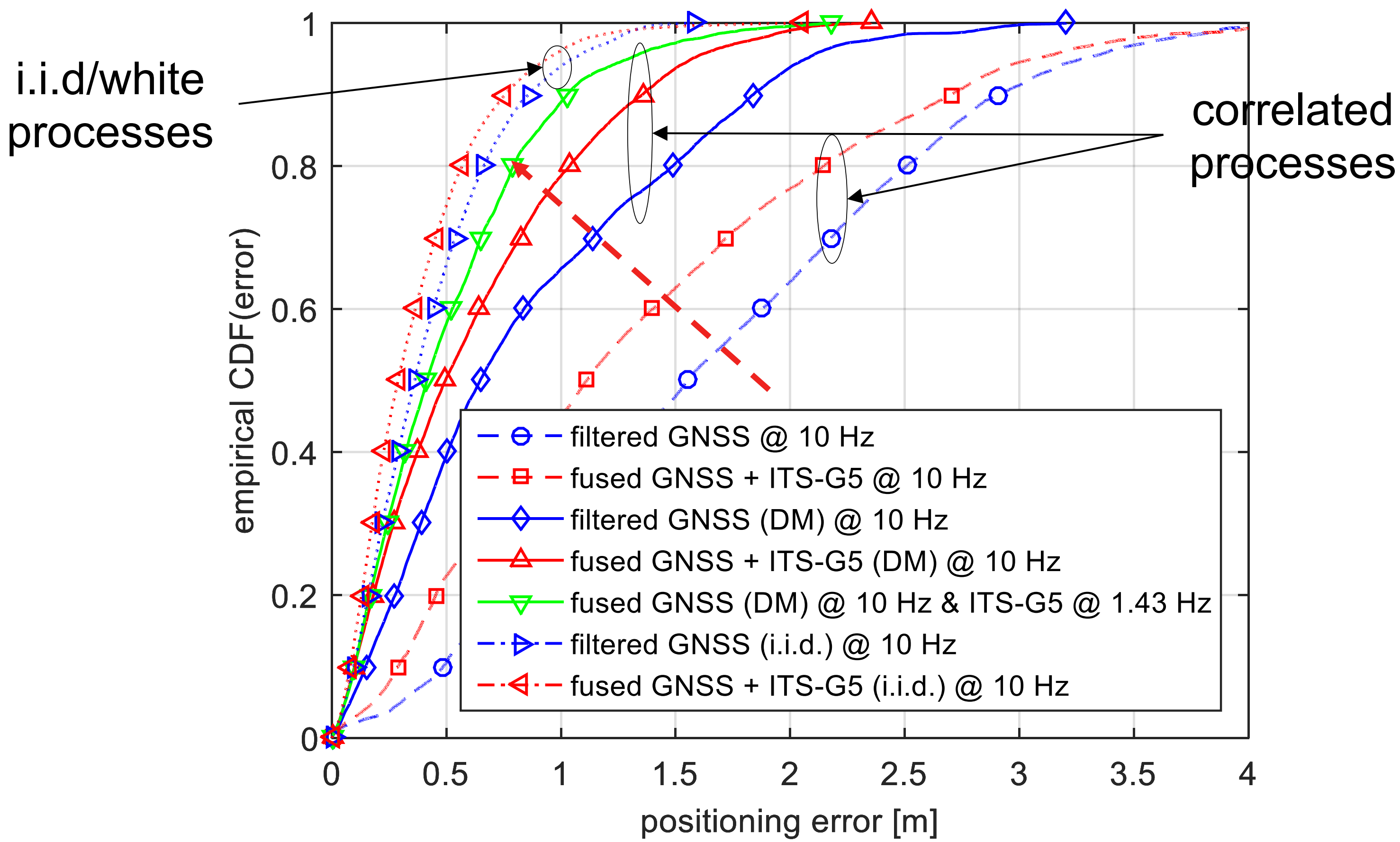
$$RSSI_{1\to E}'=RSSI_{1\to E}(k)-\lambda^{Sh}RSSI_{1\to E}(k-$$

- **Protocol level mitigation**
  - Adaptively decreased cooperative fusion rate
    → Collect uncorrelated measurements



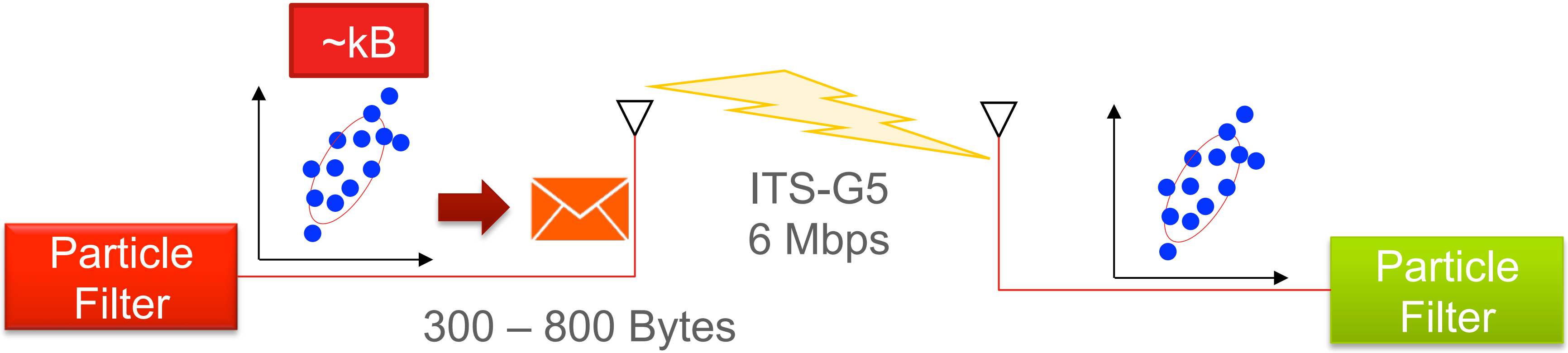
MITIGATION OF SPACE-TIME CORRELATIONS
PERFORMANCE EVALUATION

- **ECDF of localization errors for different correlation mitigation schemes in a highway scenario (steady-state mobility)**



IMPACT ON V2X COMMUNICATIONS

- **Location estimation by distributed particle filter (PF)**
  - Posterior by a set of random state samples
  - Any process nonlinearity and noise distribution
  - High number of particles, generating heavy communication load due to belief messages passing

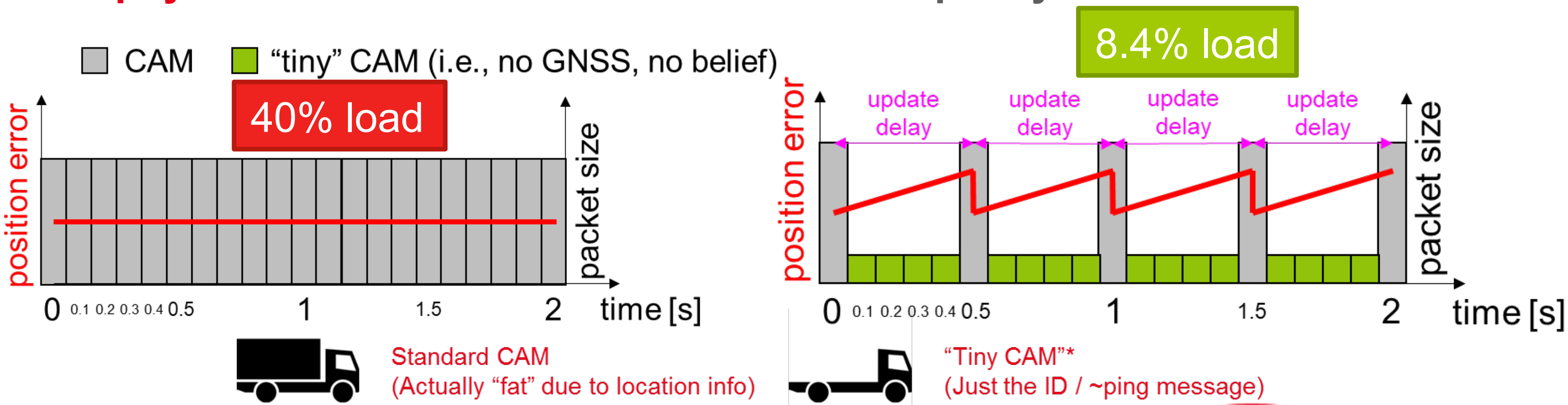


- **Challenges**
  - Limited CAM size
  - Limited channel capacity
  - ETSI Decentralized Congestion Control (DCC)
    - Reduced CAM rate (e.g., 2 Hz) → Expected accuracy degradation

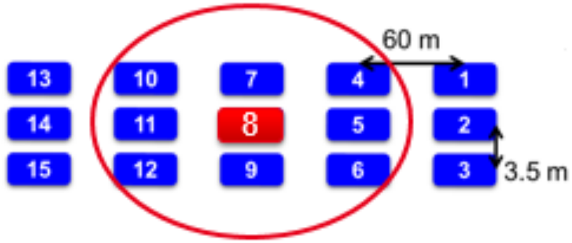
MESSAGE APPROXIMATION & TX CONTROL

- **Parametric message approximation** → **Reduce the size of particles info**

- **Tx payload/rate control** → **Standard CAM Tx policy vs. mixed CAM traffic**



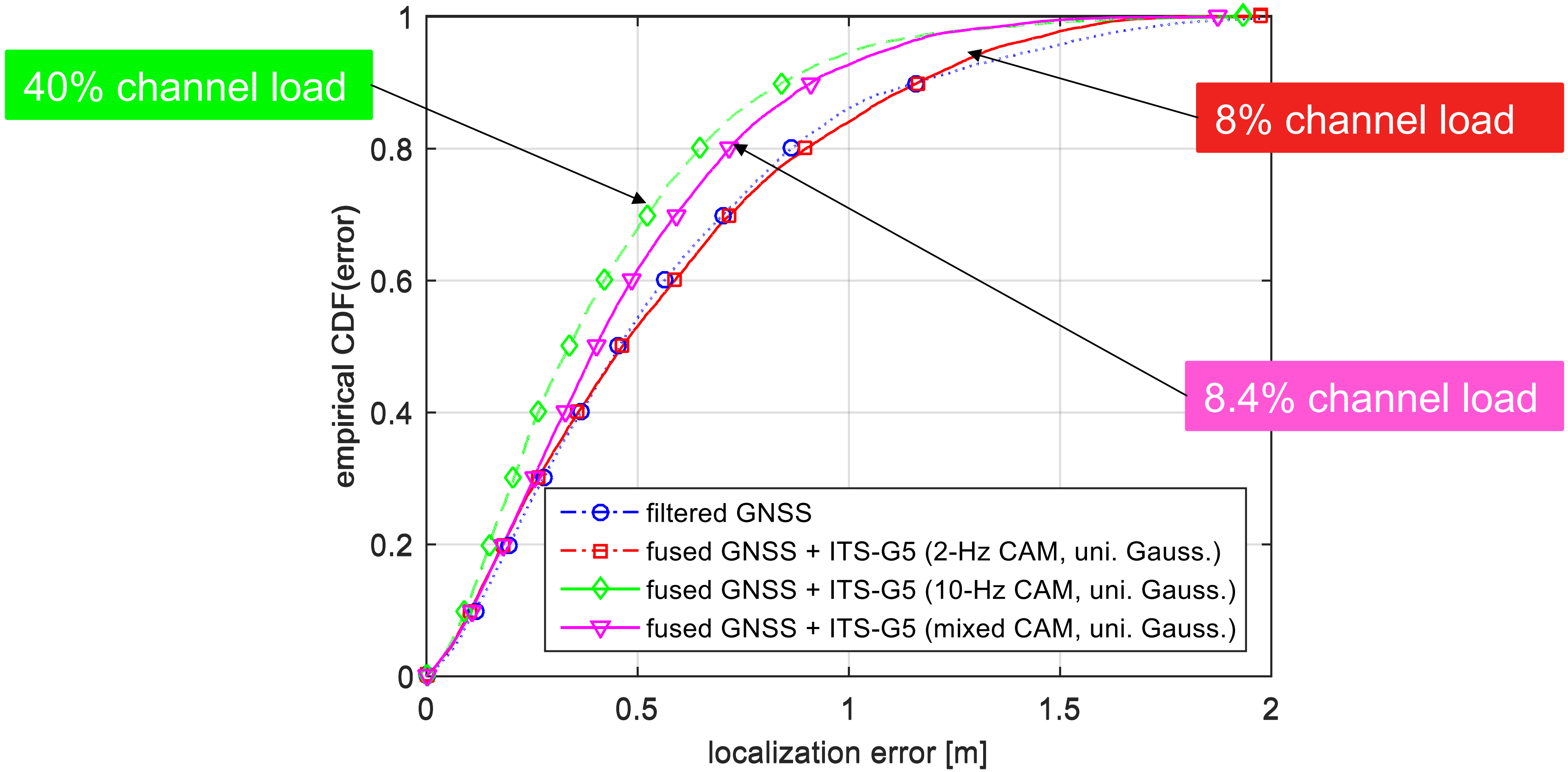
- **Tx power control** for "tiny CAMs" (for RSSI only)



[Hoang16a]

MESSAGE APPROXIMATION & TX CONTROL
PERFORMANCE EVALUATION

- **ECDF of localization errors for different message approximation and transmission control strategies (1000 particles)**



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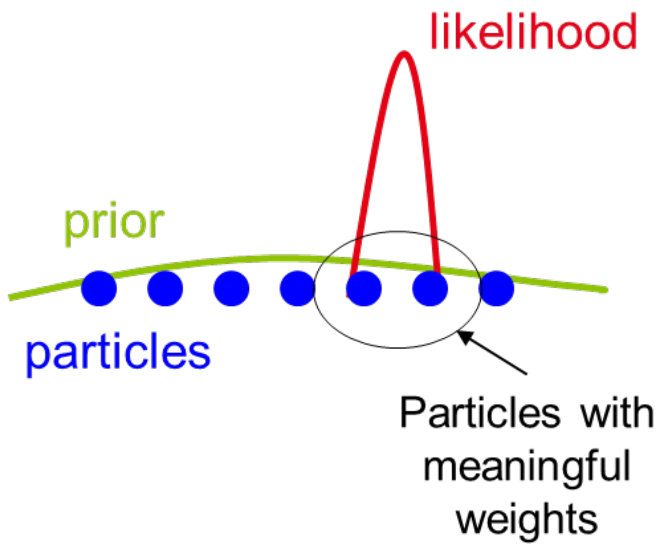
CHALLENGES TO PARTICLE FILTER BASED FUSION

- **High dimensional state and high/peaky likelihood → Harmful to PF**
  - Number of particles vs. state space
  - "Mismatch" between prior and likelihood
    - Particles depletion
    - Filter overconfidence
    - Bias propagation through CLoc

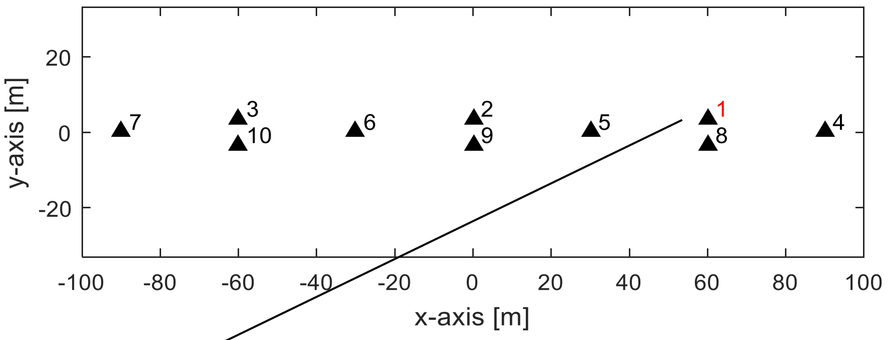


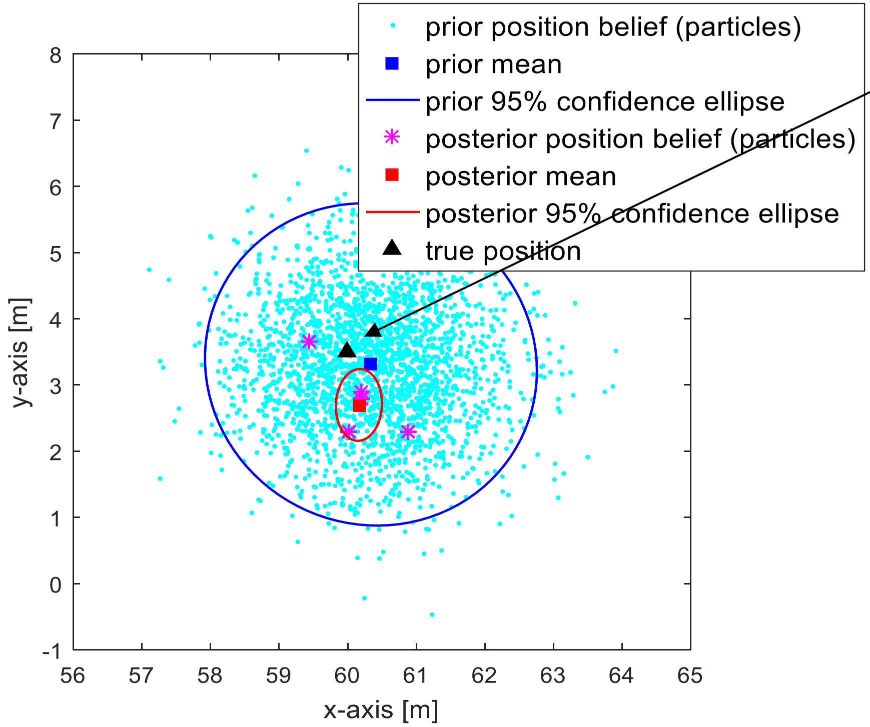
- **PF-based GNSS+IR-UWB fusion**
  - Neighbors positioned with uncertainties → High dimensional estimation space
  - Good prior not always guaranteed → Wide prior
  - Accurate ranges (e.g., IR-UWB) → Peaky likelihood

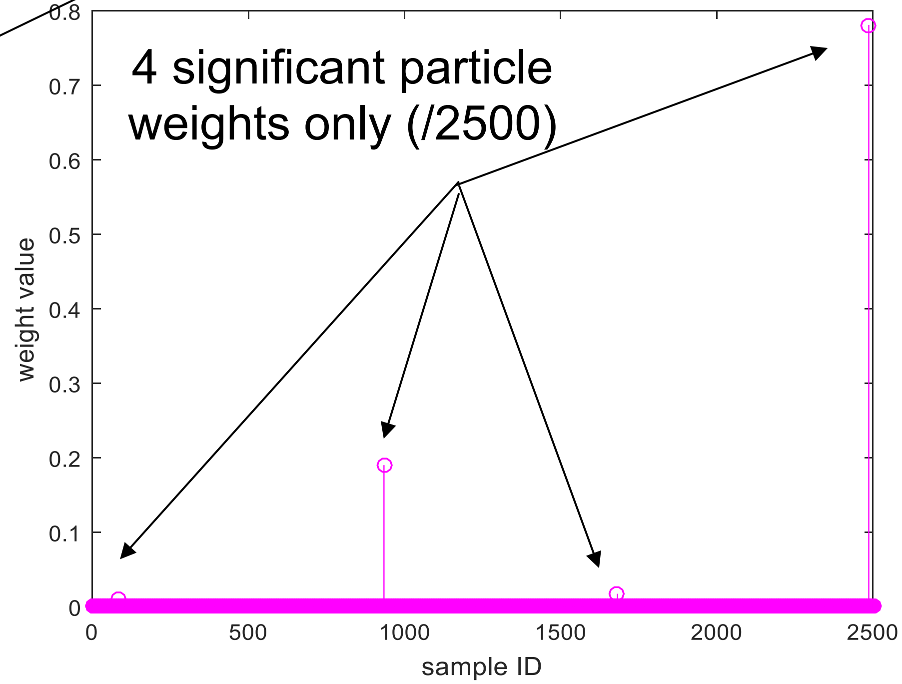
- **Questionable PF efficiency in case of IR-UWB+GNSS fusion ?**

PF DEPLETION & BIAS PROPAGATION (1)

- Ex. of **overconfidence** in biased state estimates due to particles **depletion** (**large prior vs. narrow likelihood**) with 2500 particles

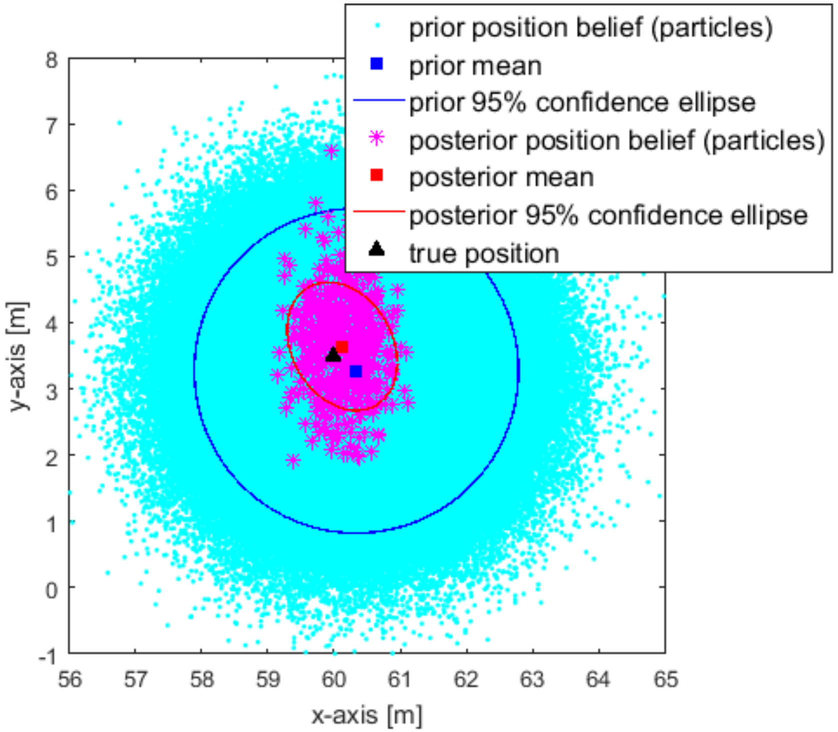


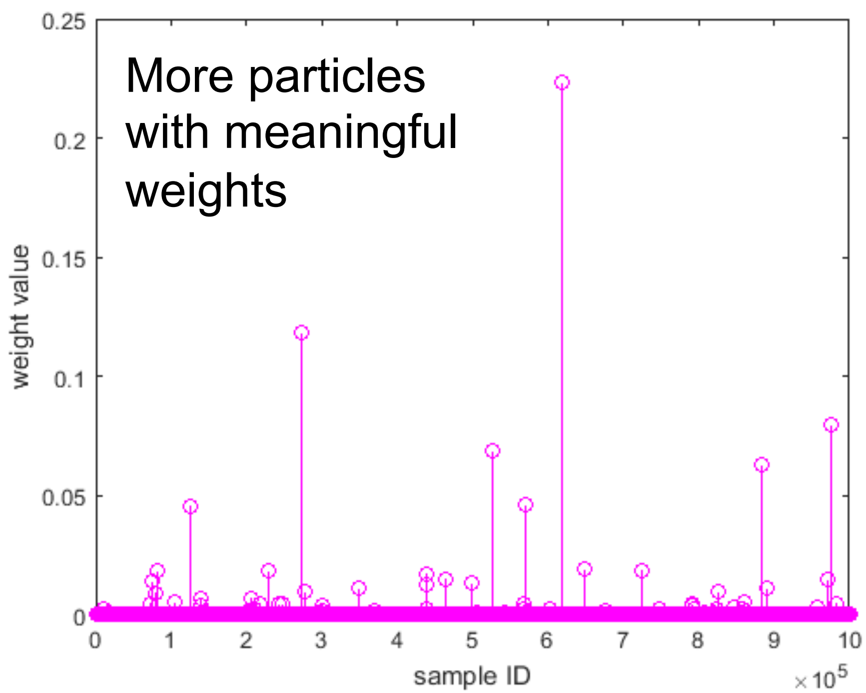




PF DEPLETION & BIAS PROPAGATION (2)

- **Ex. of unrealistically higher (10^6!) nb of particles (same scenario)**
  - More particles have meaningful weights → No more overconfidence and preserved correction power from accurate observations but…
  - Unaffordable for real-time (high computational complexity)

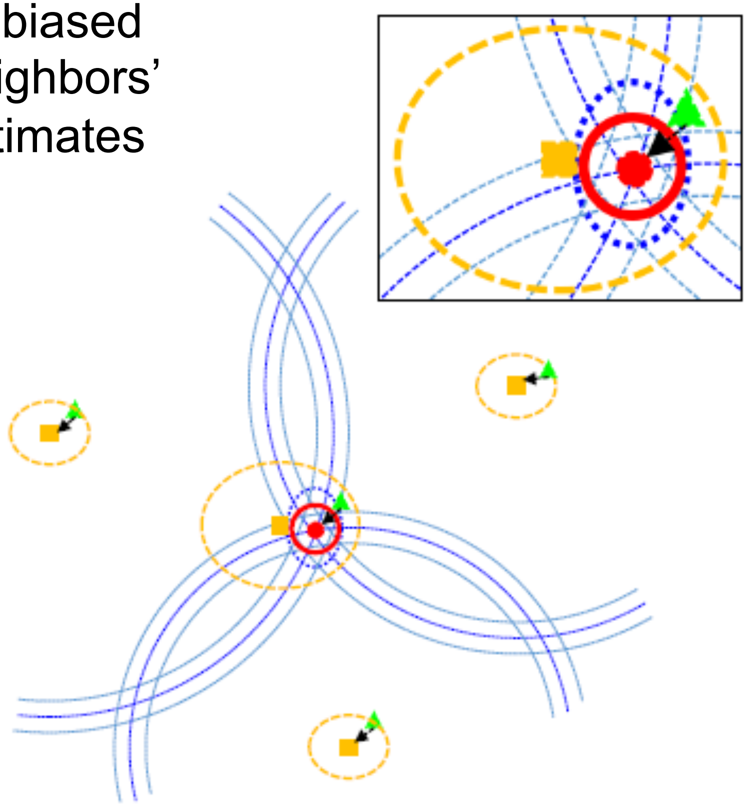


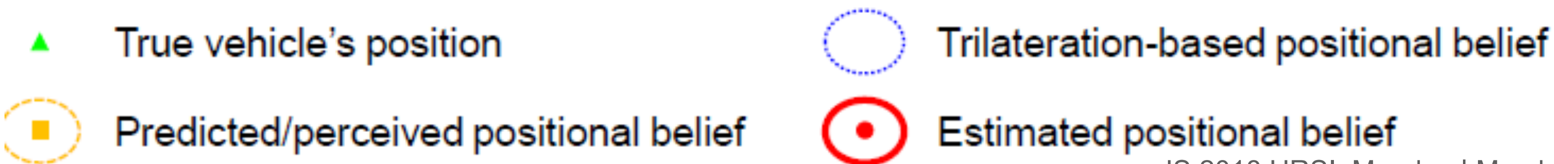


PF DEPLETION & BIAS PROPAGATION (3)

- **Bias propagation from "Virtual Anchors"**

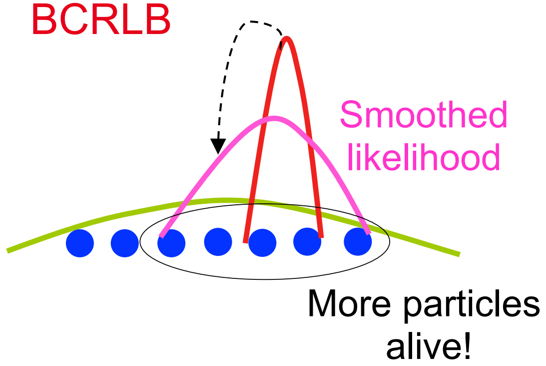
Unbiased neighbors' estimates



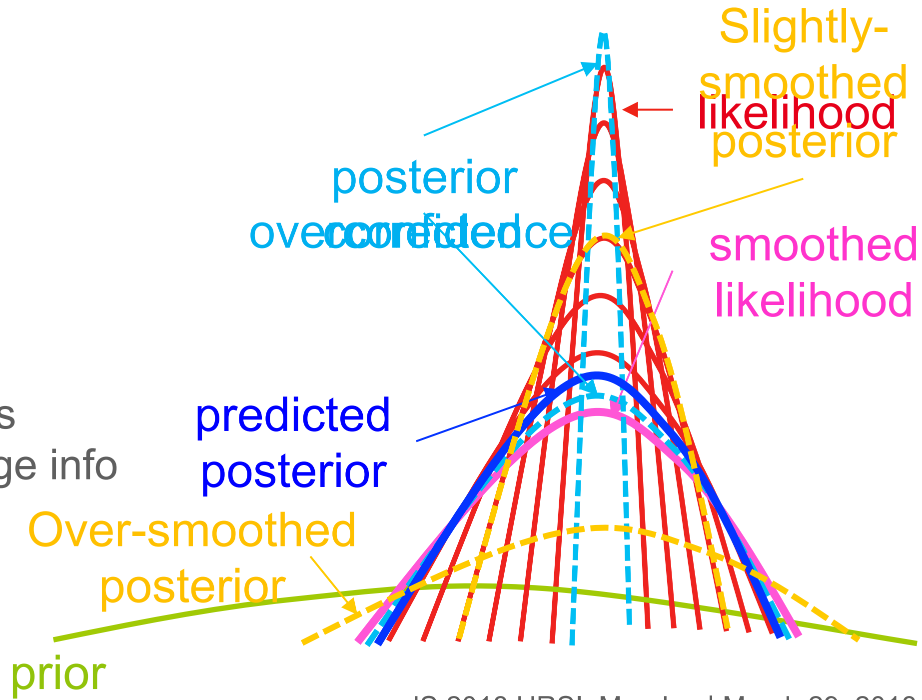


IMPROVED PF EFFICIENCY FOR HIGH DIM. ESTIMATION WITH ACCURATE V2V RANGES

- **Scheduling (heterogeneous GNSS conditions)** **[Hoang16c]**
- **Adaptive Bayesian dithering (homogenous GNSS conditions)**
  - Adaptive smoothed likelihood in perception model
    - Based on theoretical bounds e.g., BCRLB (same as for link selection)
    - Dithering noise gradually added in filter's perception so as not to outperform the BCRLB



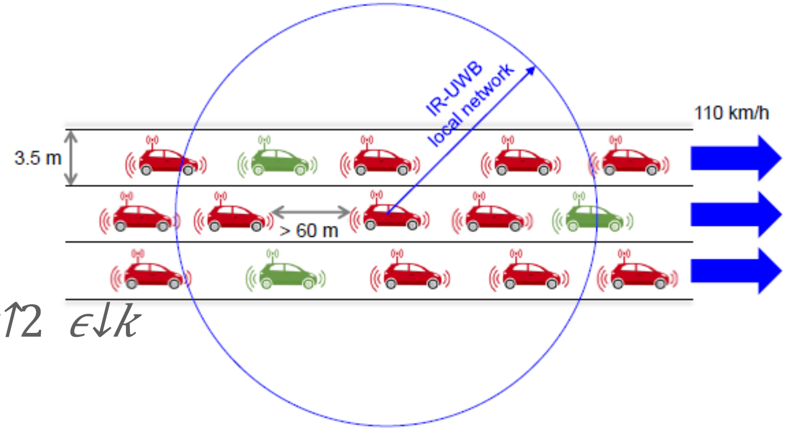
  - Main expected benefits
    - Reasonable number of particles
    - Minimized loss of accurate range info



[Hoang17a]

IMPROVED PF EFFICIENCY SETTINGS

- **Highway environment**
  - 3-lane highway
  - IR-UWB network ~ 10 neighbors
  - Gauss-Markov traffic
    $v_k = \alpha v_{k-1} + (1-\alpha)v + \sqrt{1-\alpha^2}\ \epsilon_k$



- **Main simulation parameters**

GNSS errors in x-/y-axes (1σ)	1.5 m*
IR-UWB ranging error (1σ)	0.2 m
Initial positional errors in x-/y-axes (1σ)	1 m
Initial velocity errors in x-/y-axes (1σ)	0.1 m/s
Number of particles	1000

Unbalanced noises

large prior

reasonable nb

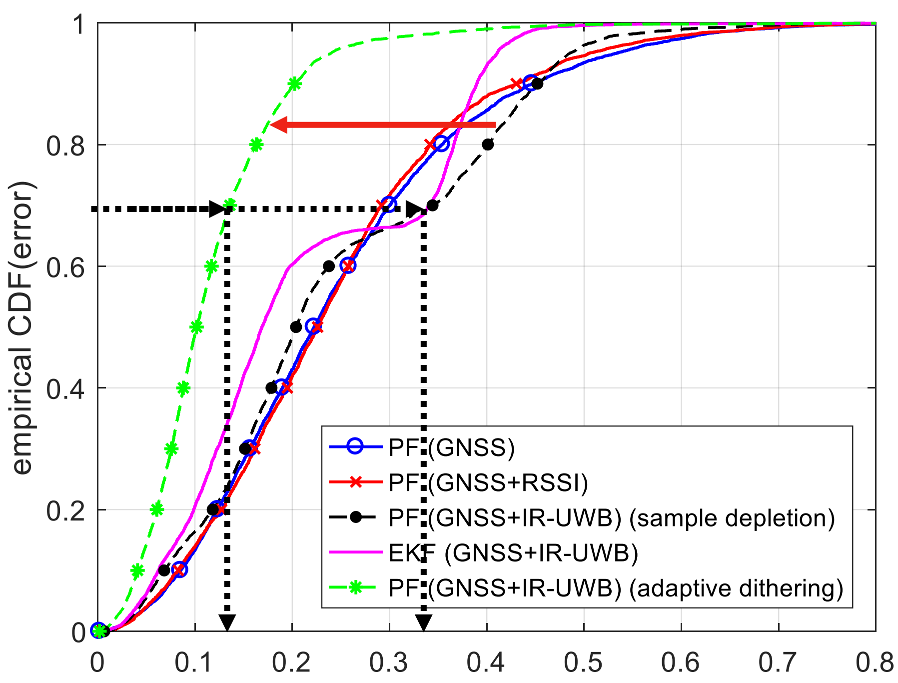
- **Performance comparisons**
  - PF (GNSS, GNSS+RSSI, GNSS+IR-UWB (part. depletion vs. adapt. dithering))
  - EKF (GNSS+IR-UWB)

*Satellite-Based Augmentation Systems (SBAS)

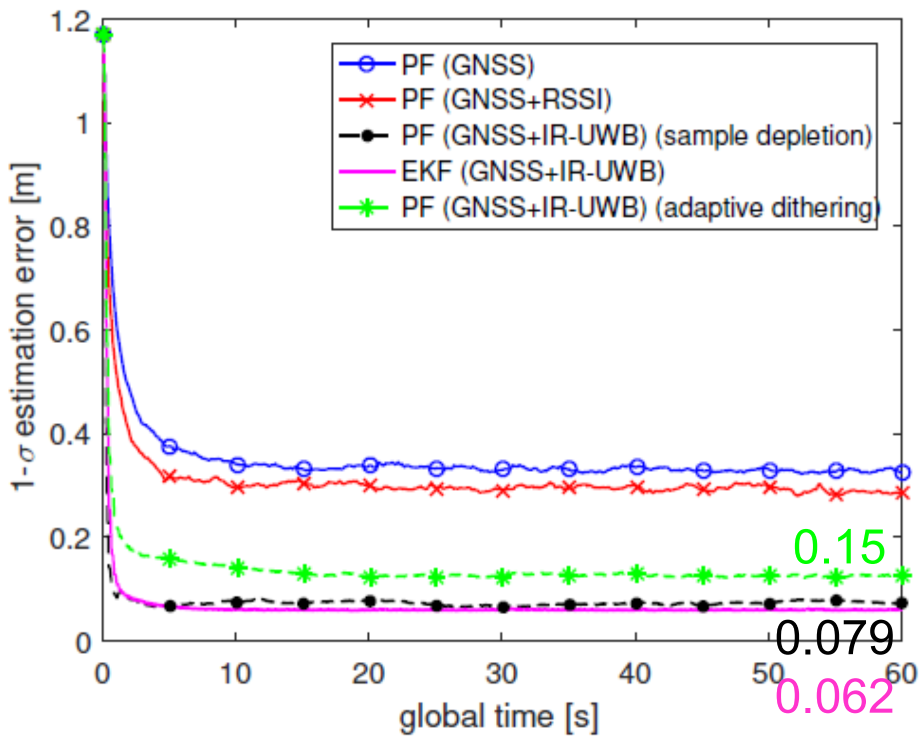
IMPROVED PF EFFICIENCY
PERFORMANCE EVALUATION

EURECOM
Sophia Antipolis

- **Over-confidence depending on both**
  - Actual 1-σ (68th percentile) localization errors
  - Perceived/Estimated 1-σ localization errors by fusion filters



0.13
0.32
0.33



→ Over-confident PF under particles depletion (id. EKF)

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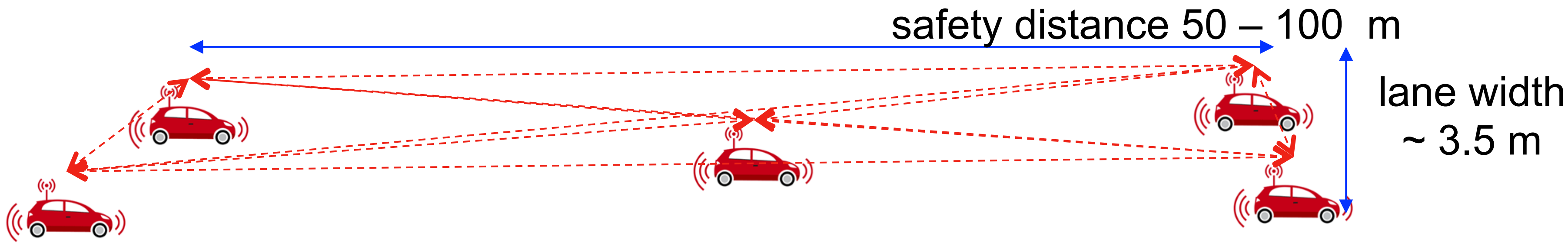
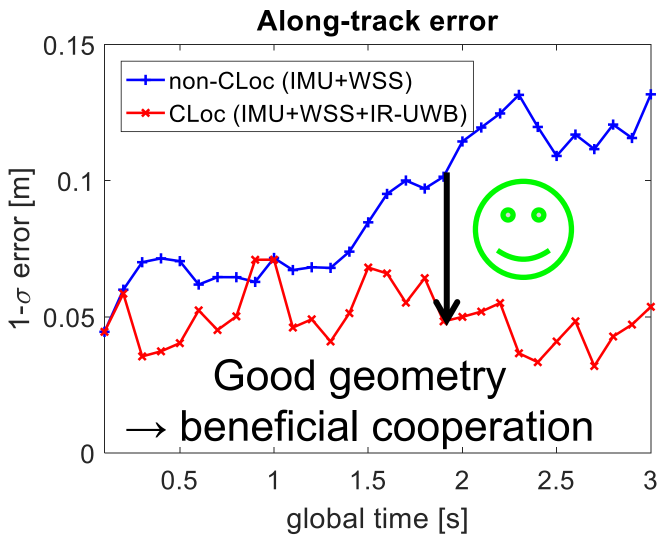
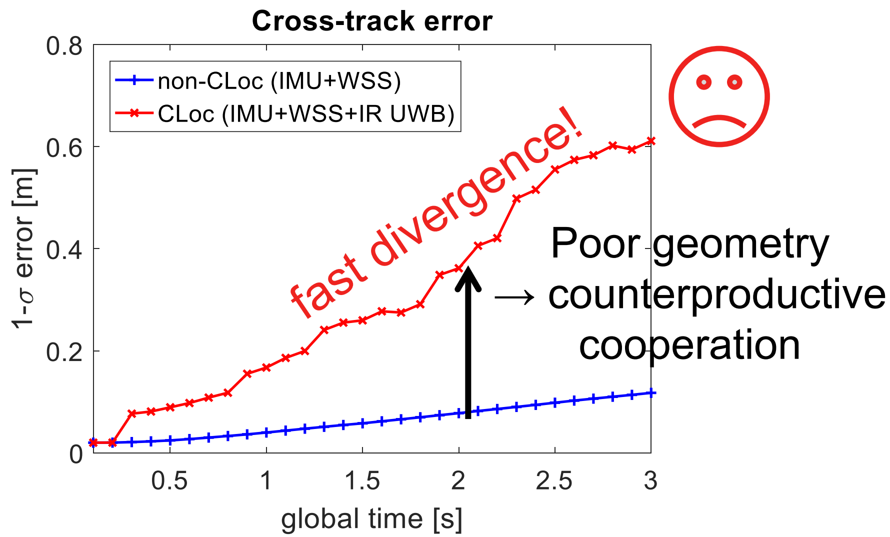
REMAINING CHALLENGES & PATHOLOGICAL CASES

- **Unbalanced vehicular geometry ~ 1-D → Singular cross-track axis**



- **Dead reckoning errors accumulation in GNSS-denied scenarios**
  → Error propagation





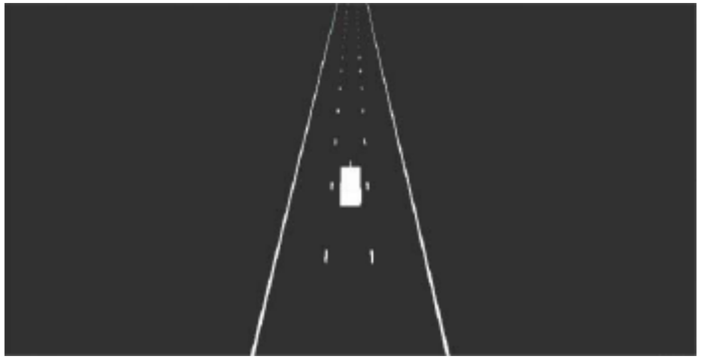
MULTISENSOR FUSION FOR IMPROVED CROSS-TRACK LOCALIZATION

- **IMU gyroscope ω_k integration**

$$x_{k+1} \approx x_k + \Delta T s_k \cos(\theta_k + 0.5 \Delta T \omega_k)$$
$$y_{k+1} \approx y_k + \Delta T s_k \sin(\theta_k + 0.5 \Delta T \omega_k)$$
$$\theta_k = \theta_k + \Delta T \omega_k$$

Prediction step in PF

- **Camera-based lane detection**



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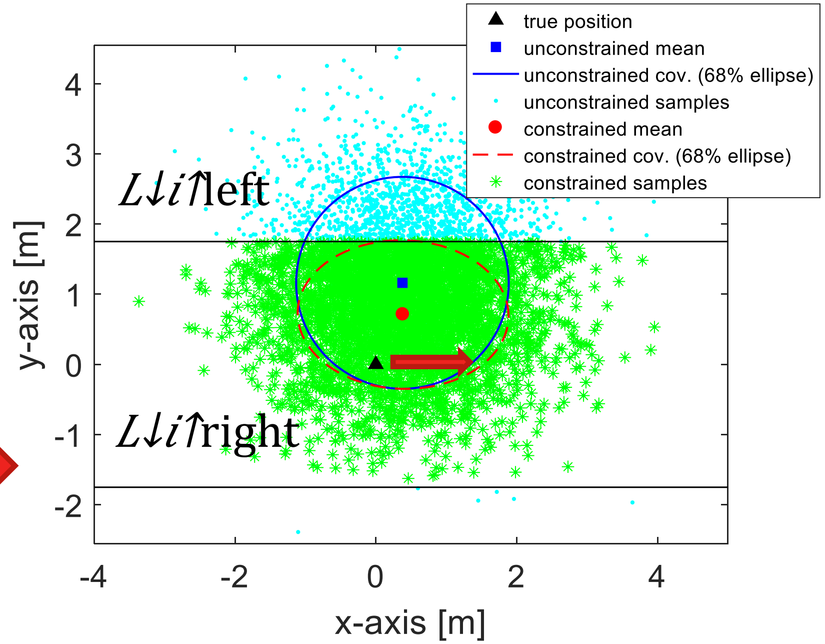


$$L_i^{right} < \boldsymbol{X}_i^{(particle)} < L_i^{left}$$

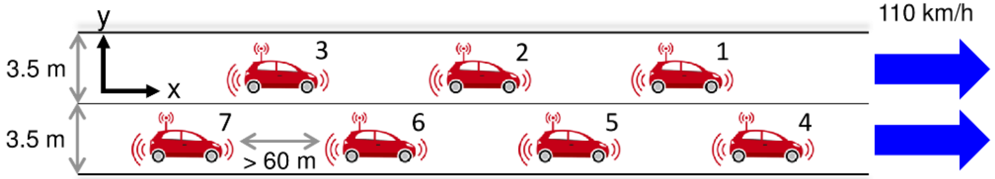
$$X_i^{(particle)} \geq L_i^{left},$$
$$X_i^{(particle)} \leq L_i^{right}$$

[Hoang17b]

IMPROVED CROSS-TRACK ERRORS SETTINGS

- **Highway environment**
  - 2-lane highway, 7 vehicles
  - Gauss-Markov mobility traffic

$$v_k = \alpha v_{k-1} + (1-\alpha) v + \sqrt{1-\alpha^2}\ \epsilon_k$$

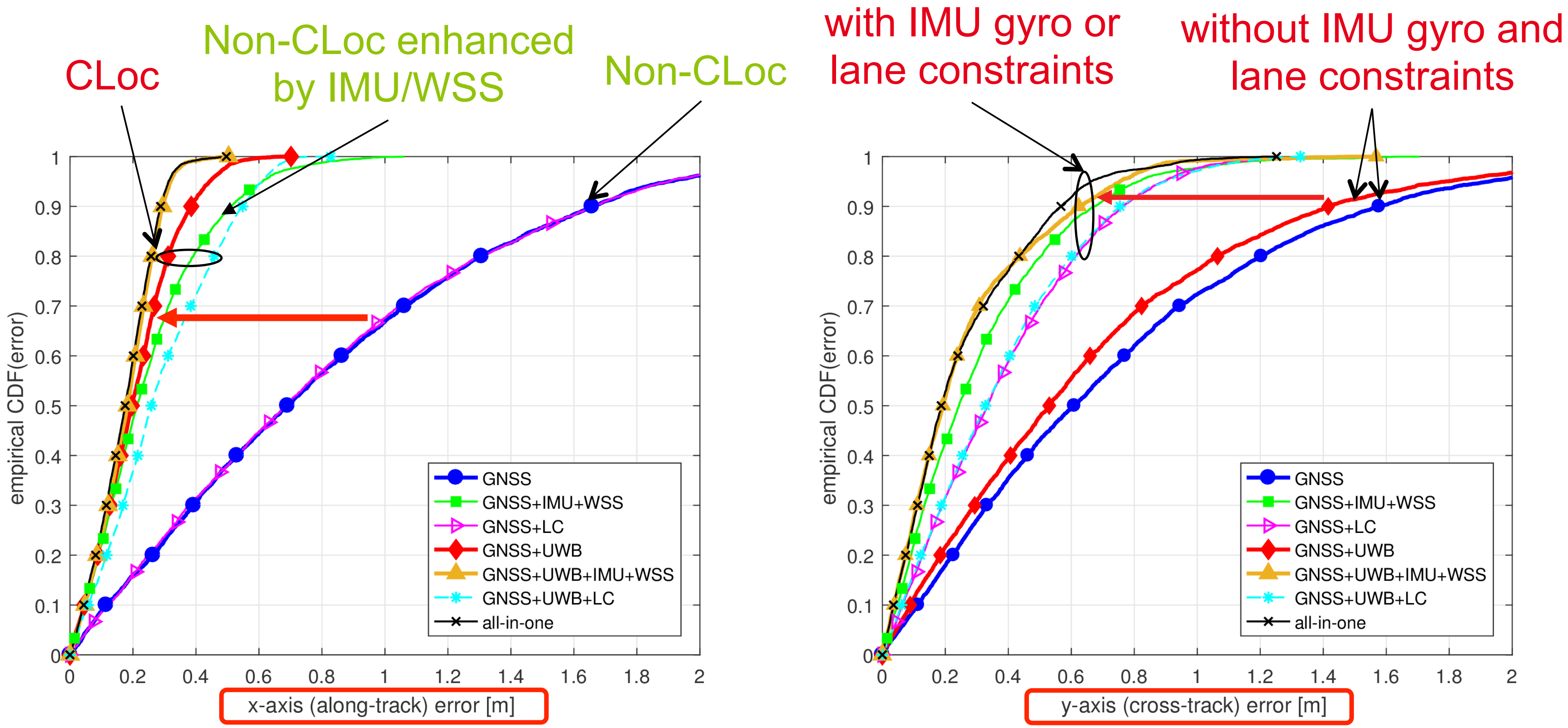


- **Performance comparisons**
  - 2 main configurations: **non-CLoc** vs. **CLoc (V2V IR-UWB)**

GNSS	**Non-CLoc**
GNSS + IMU + WSS	**Non-CLoc**
GNSS + lane constraints	**Non-CLoc**
GNSS + **V2V IR-UWB**	**CLoc**
GNSS + **V2V IR-UWB** + IMU + WSS	**CLoc**
GNSS + **V2V IR-UWB** + lane constraints	**CLoc**
GNSS + **V2V IR-UWB** + IMU + WSS + lane constraints	**CLoc**

IMPROVED CROSS-TRACK ERRORS PERFORMANCE EVALUATION

- **ECDF of 1-D localization errors along x (left) and y (right) axes**



Individual information source affects each component of position error differently

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CONCLUSIONS

- Sub-meter accuracy through CLoc with existing technologies?
  - (Conditionally) yes !
    - Typically, precision improved from 2 m down to 30 cm in 80% in most favorable simulated scenarios
  - Various challenges inherent to the cooperative vehicular context
    - Information asynchronism
    - Space/time measurement correlations
    - Computational complexity and information selection
    - Communication constraints (imposed by underlying standards)
    - Relative geometry
  - Other open questions ahead (future work)
    - Context-aware cooperative fusion (large-scale/long-term)
    - Security and privacy of involved V2X cooperative links
    - Fusion partitioning and data kind (e.g., wrt. juridical responsibility → See autonomous cars accidents)
    - New location-enabled applications and services (mapping/cartography, automotive IoT, crowd sensing…)

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EXPERIMENTAL VALIDATIONS

EURECOM
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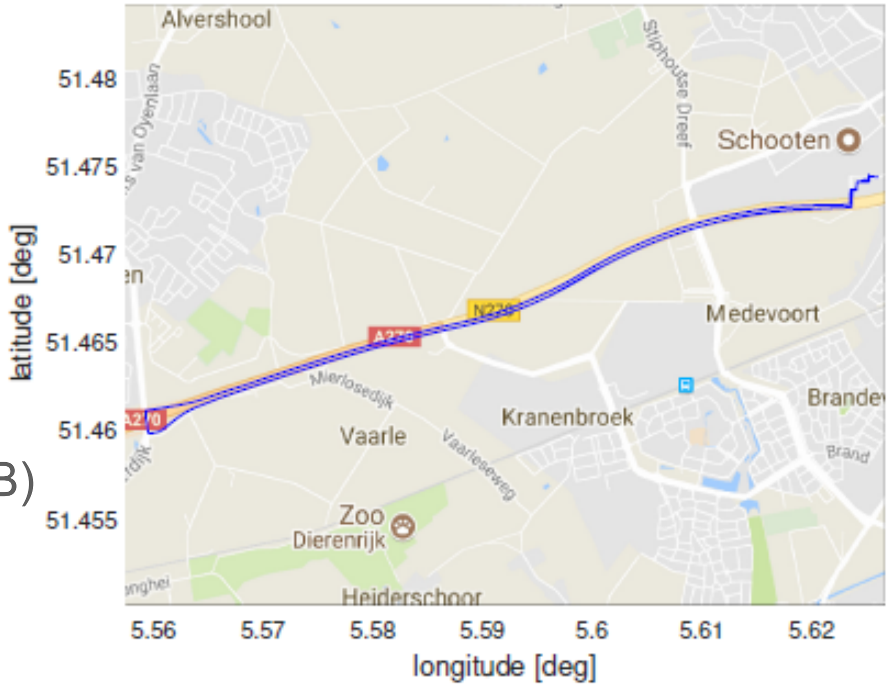
HIGHTS
High precision positioning for Cooperative-ITS
http://hights.eu
(H2020 - 636537)

- **Large-scale field trials in Helmond, Netherlands**
  - 4 vehicles with varying fleet topology over long-term trajectories (multiple trips of several kms each)
    - RTK GPS → Ground truth
    - Singe-band GPS
    - ITS-G5 platform (Cohda MK5) → V2V data (+ RSSI)
    - IR-UWB tag → V2V RT-ToF



- **Performance comparison**
  - Non-Cloc → Standalone GPS+IMU)
  - CLoc → GPS+IMU+ITS-G5+IR-UWB)

- **Processing of collected data currently in progress**

RELATED CONTRIBUTIONS

- **Journal**
  - **[Hoan16b]** G.M. Hoang, B. Denis, J. Härri, D. Slock, "Breaking the gridlock of spatial correlation in GPS-aided IEEE 802,11p-based cooperative positioning," IEEE Trans. on Vehicular Technology, Connected Vehicles Series, **Aug. 2016**

- **Conferences**
  - I. Khan, G.M. Hoang, J. Härri, D. Slock, "Rethinking cooperative awareness for future V2X safety-critical applications," Proc. VNC'17, **Nov. 2017**
  - G.M. Hoang, B. Denis, J. Härri, D. Slock, "Robust data fusion for cooperative vehicular localization in tunnels," Proc. IV'17, **June 2017**
  - **[Hoang17b]** G.M. Hoang, B. Denis, J. Härri, D. Slock, "Mitigating unbalanced GDoP effects in range-based vehicular cooperative localization," Proc. ICC'17-ANLN, **May 2017**
  - **[Hoan17a]** G.M. Hoang, B. Denis, J. Härri, D. Slock, "Robust and low complexity Bayesian data fusion for hybrid cooperative vehicular localization," Proc. ICC'17, **May 2017**
  - **[Hoan16c]** G.M. Hoang, B. Denis, J. Härri, D. Slock, "Cooperative localization in GNSS-aided VANETs with accurate IR-UWB range measurements," Proc. WPNC'16, **Oct. 2016**
  - **[Hoan16a]** G.M. Hoang, B. Denis, J. Härri, D. Slock, "On Communication Aspects of Particle-Based Cooperative Localization in GPS-aided VANETs", Proc. CCP-IV'16, **June 2016**
  - **[Hoan15b]** G.M. Hoang, B. Denis, J. Härri, D. Slock, "Select Thy Neighbors: Low Complexity Link Selection for High Precision Cooperative Vehicular," Proc. VNC'15, **Dec. 2015**
  - **[Hoan15a]** G.M. Hoang, B. Denis, J. Härri, D. Slock, "Distributed Links Selection and Data Fusion for Cooperative Positioning in GPS-aided IEEE 802.11p VANETs," Proc. WPNC'15, **March 2015**

HIGHTS

High precision positioning for Cooperative-ITS

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Thank you!

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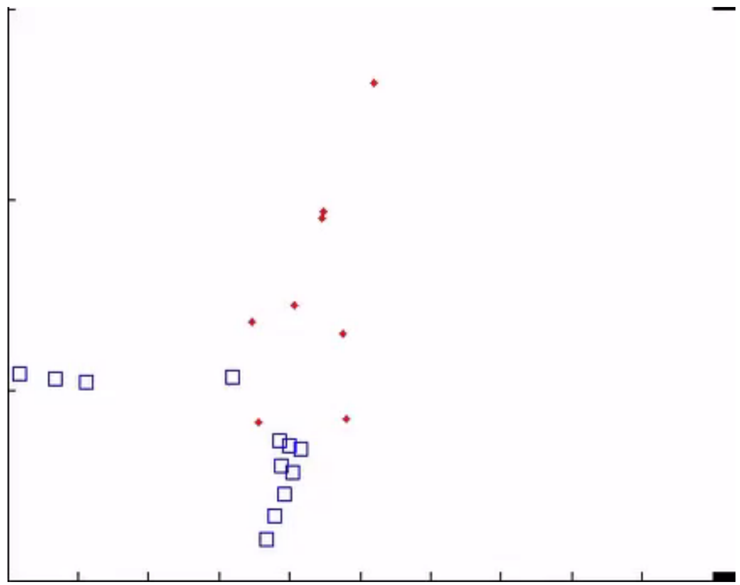
INSTITUT CARNOT CEA LETI

VALIDATION BASED ON MOBILITY TRACES SETTINGS

- **Simulation of Urban MObility (SUMO) traffic**
  - Wide-scale urban case calibrated for the city of Bologna
  - 10 vehicles' trajectories forming a consistent group for 100 s

GNSS cond.	Nominal	Slightly degraded		Severely degraded	lost
Color	$1\sigma_{GPS}$	$2\sigma_{GPS}$	$2\sigma_{GPS}$	$5\sigma_{GPS}$	

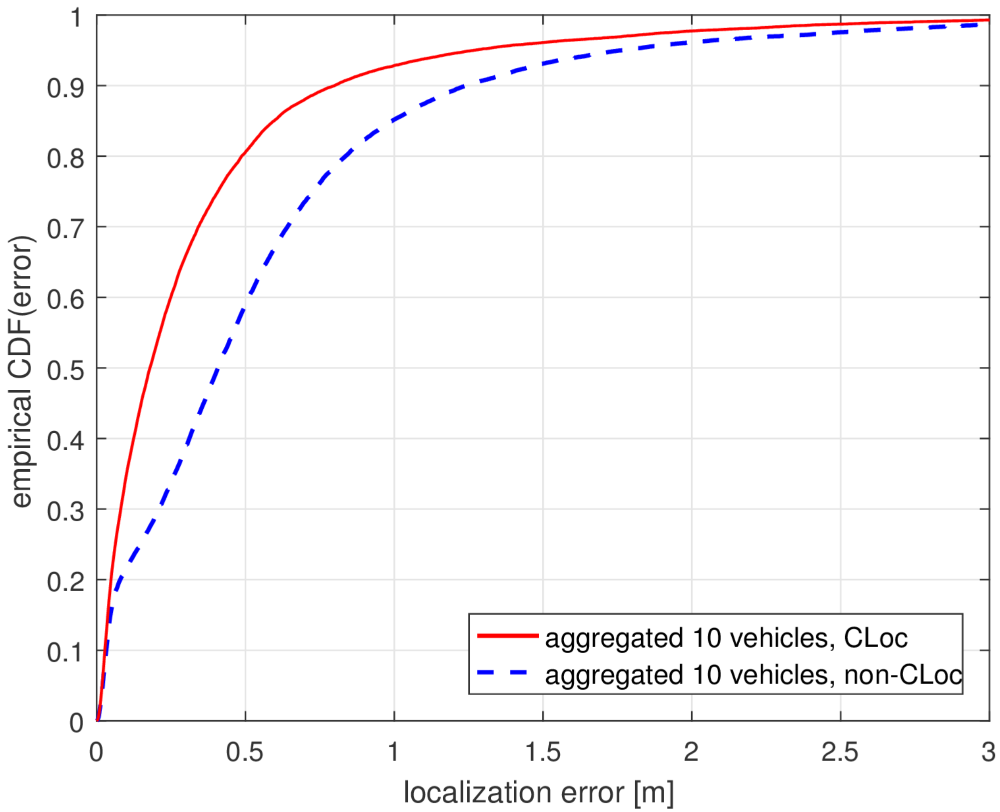


- **Key points**
  - Various GNSS classes (SPS, SBAS, DGNSS, RTK) and varying operating conditions (σx1 to σx5 and even lost)
  - Erratic mobility (intersections, lane changing…)

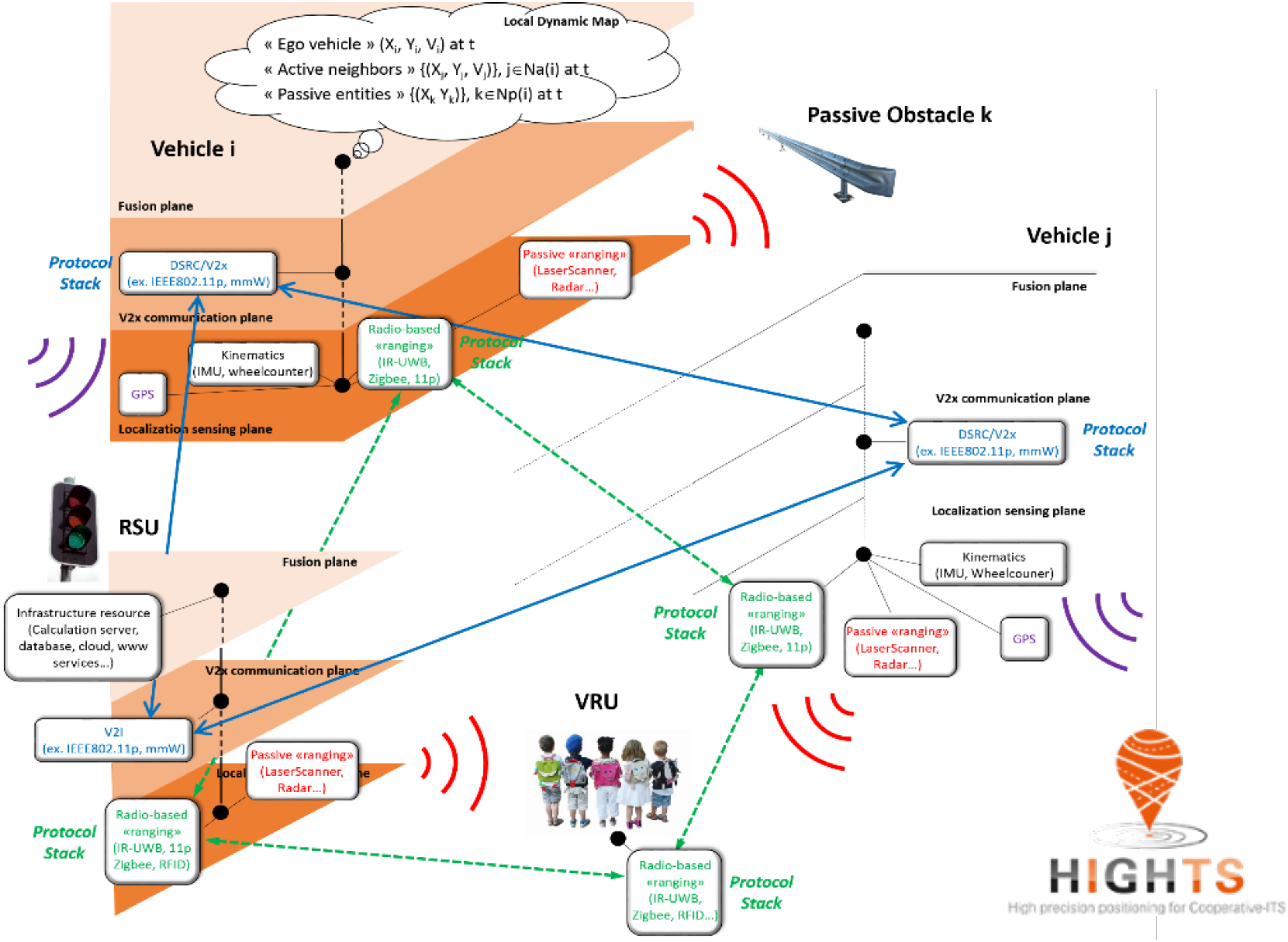
- **Performance comparison**
  - Non-CLoc (GNSS+IMU+WSS)
  - CLoc (GNSS+IR-UWB+IMU+WSS)

VALIDATION BASED ON MOBILITY TRACES
PERFORMANCE EVALUATION

- **ECDF of localization errors over all 10 vehicles**
  - Median error of 0.18 m
  - Sub-meter (0.75 m) worst-case accuracy at 90%

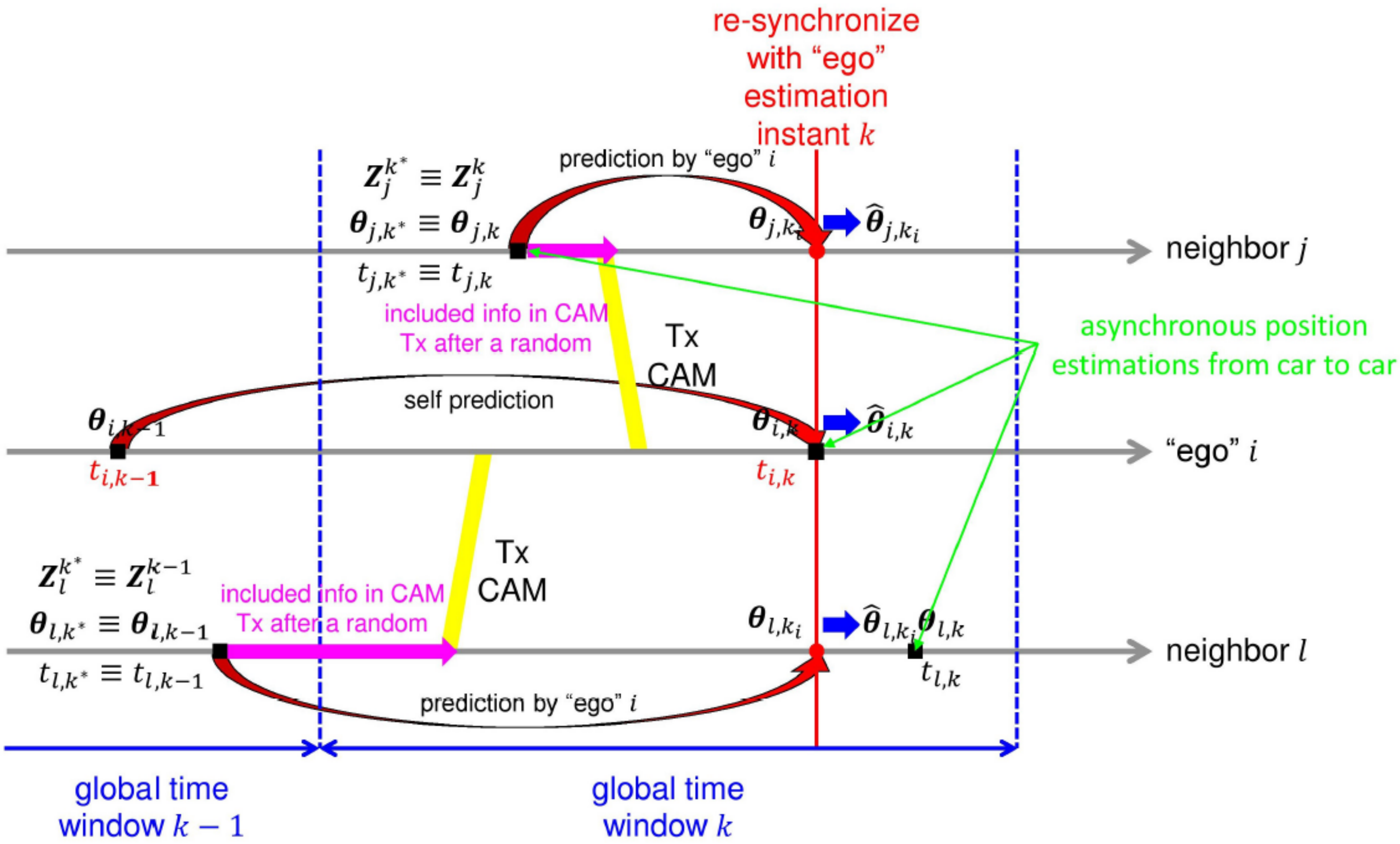


HIGHTS' OVERALL ARCHITECTURE AND PARADIGM



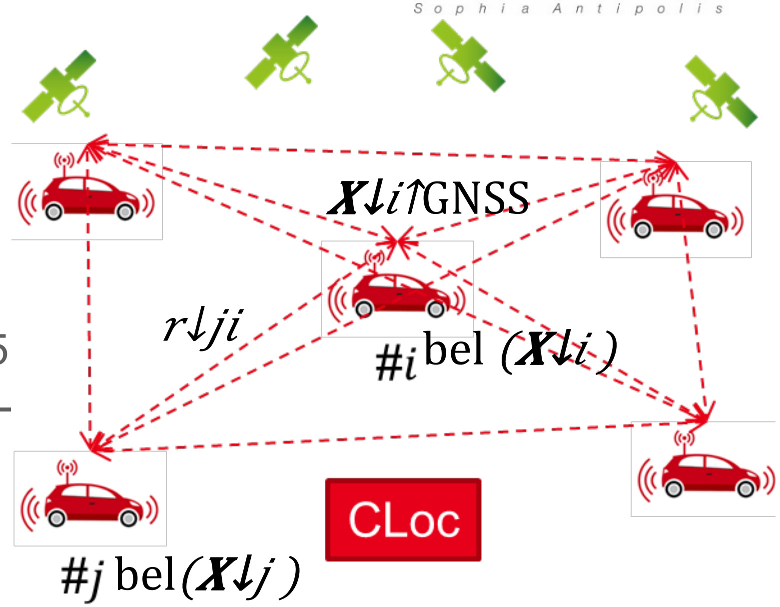
TIME RE-ALIGNMENT OF RECEIVED COOPERATIVE DATA

- Proposal: Prediction of both ego and neighbours' positions based on specific mobility models (e.g., Gauss-Markov)

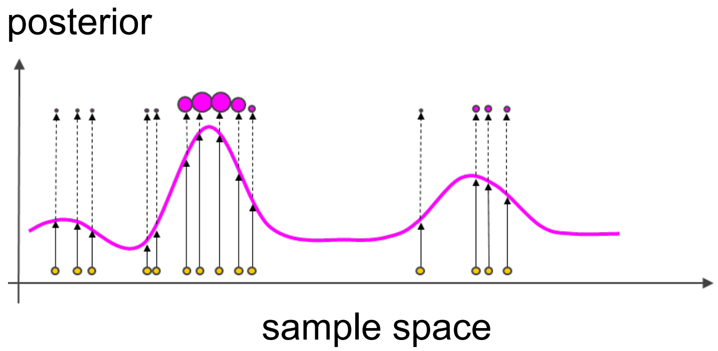


V2V COOPERATIVE FILTERING APPROACH

- **Info available for "ego" vehicle i at time $t_{i,k}$**
  - Prior "ego" belief bel $(X_i(t_{i,k}))$ → Mobility
  - "Ego" position $X_i^{GNSS}(t_{i,k})$ → GNSS
  - Neighbors' beliefs bel$(X_j(t_{j,k}))$ → ITS-G5
  - V2V ranges $r_{ji}(t_{j,k} < t_{ji,k} < t_{i,k})$ → IR-UWB



- **Goal**
  - Estimate the "ego" vehicle's state vector (2D position, speed, etc.) $X_i(t_{i,k})$ of posterior bel$(X_i(t_{i,k}))$ from prior bel $(X_i(t_{i,k}))$ using **distributed bootstrap particle filter**



- **Why choosing a bootstrap particle filter ?**
  - Particle filter (PF)
    - Posterior by a set of random state samples

    → Non-linear & non-Gaussian processes
  - Bootstrap
    - Prediction by mobility
    - Correction by likelihood

    → Simple implementation

PARTICLE FILTER STEPS

- **For vehicle i at time $t_{i,k}$, wrt. a set $\mathcal{A}_{i,k}$ of "virtual anchors"**
  - Inputs:
    - Local info: "Ego" belief $\mathrm{Bel}(\boldsymbol{X}_i(t_{i,k-1}))$ and GNSS positon $\boldsymbol{X}_i^{\mathrm{GNSS}}(t_{i,k})$
    - External info: $\forall j \in \mathcal{A}_{i,k}$, neighboring belief $\mathrm{Bel}(\boldsymbol{X}_j(t_{j,k}))$ and V2V meas. $r_{j \to i}$
  - Mobility-based prediction at both "ego" and neighboring vehicles (→ compensate for received data asynchronism)

$$\mathrm{Bel}(\boldsymbol{X}_i(t_{i,k})) = \int p\,\boldsymbol{X}_i(t_{i,k})\,\boldsymbol{X}_i(t_{i,k-1})\ \mathrm{Bel}(\boldsymbol{X}_i(t_{i,k-1}))\,d\boldsymbol{X}_i(t_{i,k-1})$$

$$\mathrm{Bel}(\boldsymbol{X}_j(t_{i,k})) = \int p\,\boldsymbol{X}_j(t_{i,k})\,\boldsymbol{X}_j(t_{j,k})\ \mathrm{Bel}(\boldsymbol{X}_j(t_{j,k}))\,d\boldsymbol{X}_j(t_{j,k})$$

  - Likelihood-based particle weights correction
    $w_{i,k} \propto p\,\boldsymbol{X}_i^{\mathrm{GNSS}}(t_{i,k}), \ldots r_{j \to i} \ldots \mathrm{Bel}(\boldsymbol{X}_i(t_{i,k})), \ldots \mathrm{Bel}(\boldsymbol{X}_i(t_{i,k})) \ldots$
  - Output: MMSE estimator $\hat{\boldsymbol{X}}_i(t_{i,k}) = \mathrm{MMSE}(\mathrm{Bel}(\boldsymbol{X}_i(t_{i,k})), w_{i,k})$

LINK SELECTION STRATEGIES
BAYESIAN CRLB – A CLOSER LOOK

- **Bayesian CRLB (BCRLB) solution**

$$\mathbf{BCRLB}_E = (J_E^B)^{-1}$$

- **Bayesian Information Matrix**

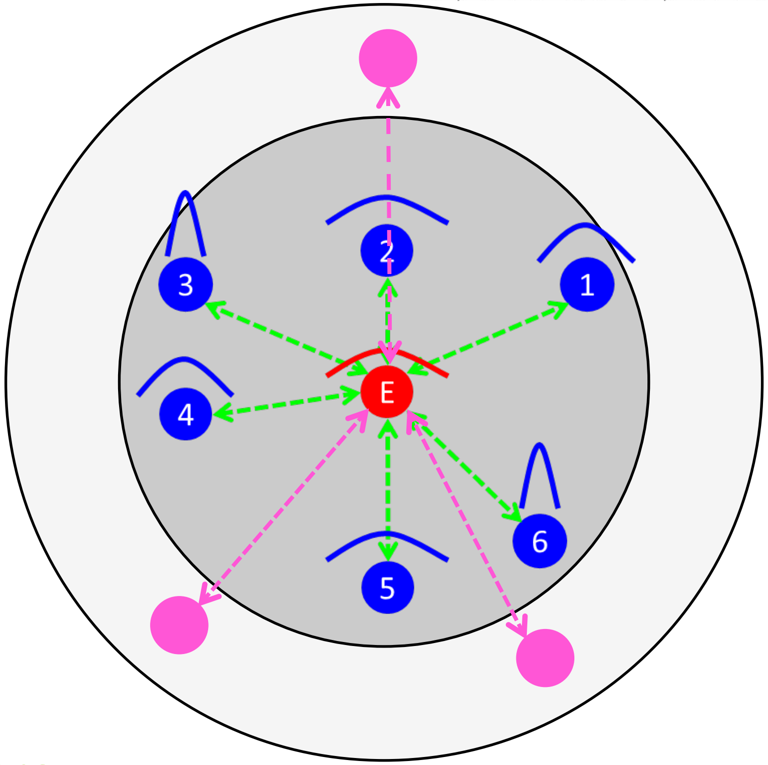
$$\boldsymbol{J}_E^B = \boldsymbol{J}_E^P + \sum_{i=1}^{N} \left[(\boldsymbol{J}_i^P)^{-1} + (\boldsymbol{J}_{i\rightarrow E}^{M})^{-1} \right]^{-1}$$

"Ego" prior info Neighbors' prior info Measurement info

$$\boldsymbol{J}_i^P = -\mathbb{E}_{\boldsymbol{X}_i}\left[\partial^2 \log p(\boldsymbol{X}_i) / \partial(\boldsymbol{X}_i)^2\right] = \mathrm{Var}(\boldsymbol{X}_i)^{-1}$$

3. neighboring uncertainty (from CAM info)

Gaussian approximations



2. relative geometry

$$\boldsymbol{J}_{i\rightarrow E}^{M} = -\mathbb{E}_{\mathrm{RSSI},\boldsymbol{X}_E,\boldsymbol{X}_i}\left[\partial^2 \log p(\mathrm{RSSI}_i \mid \boldsymbol{X}_E,\boldsymbol{X}_i) / \partial(\boldsymbol{X}_E)^2\right] = \mathbb{E}_{\boldsymbol{X}_E,\boldsymbol{X}_i}\left[b(\boldsymbol{X}_E - \boldsymbol{X}_i)(\boldsymbol{X}_E - \boldsymbol{X}_i \ldots\right]$$

Estimate using Monte Carlo integration

1. Radio link quality

$$b = (10 n_p / \sigma_{Sh} \log 10 \ldots)$$