Cooperative Simultaneous Localization and Tracking (CoSLAT) with Reduced Complexity and Communication

Florian Meyer[1], *Franz Hlawatsch*[1], *and Henk Wymeersch*[2]

[1]Institute of Telecommunications, Vienna University of Technology, Austria
[2]Department of Signals and Systems, Chalmers University of Technology, Gothenburg, Sweden

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Outline

- Introduction
- CoSLAT System Model
- Message Passing Scheme
- Hybrid Particle-based/Parametric Belief Propagation
- Distributed CoSLAT Algorithm
- Simulation Results
- Conclusion

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- The recently introduced framework of cooperative simultaneous localization and tracking (CoSLAT) provides a coherent combination of cooperative sensor self-localization (CSL) and distributed target tracking (DTT) [Meyer et al., 2012]

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Contribution:

We propose an **advanced hybrid nonparametric (particle-based) and parametric message passing algorithm for CoSLAT** in which communication and computation costs are significantly reduced

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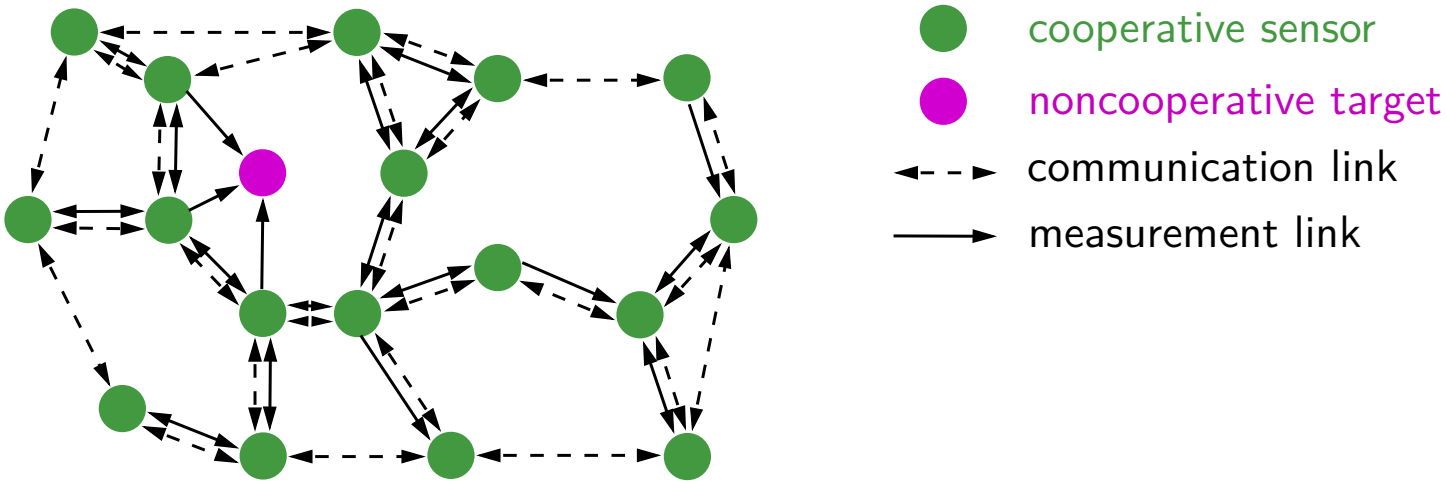
- We consider a sensor network consisting of K cooperative sensor nodes (indexed by $k \in \{1, \ldots, K\}$) and a noncooperative target node (indexed by $k = 0$)



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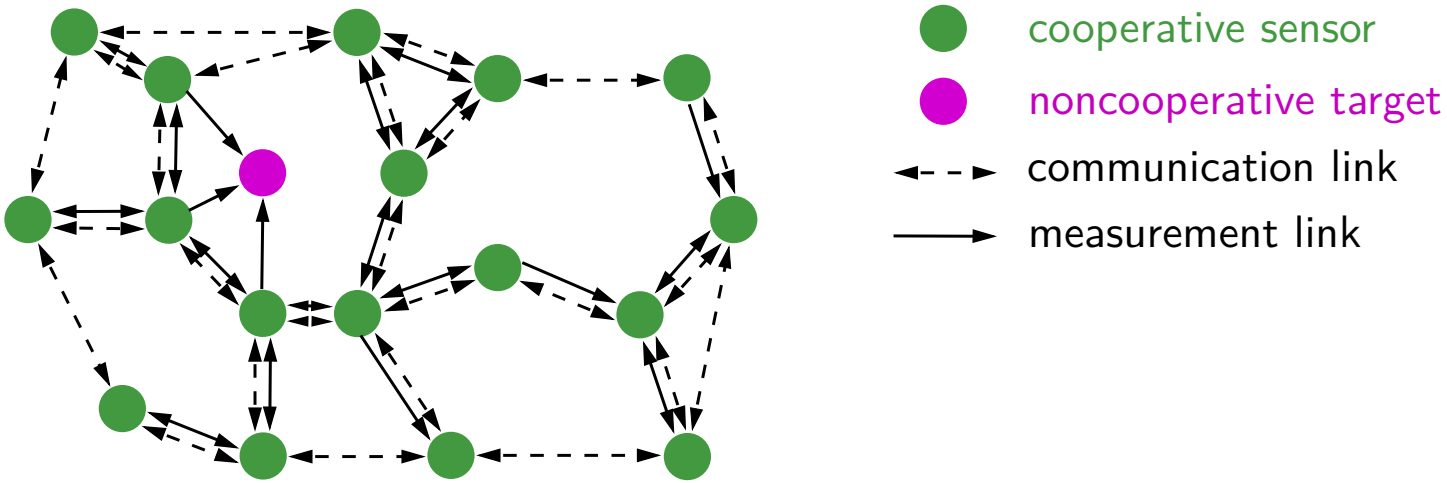

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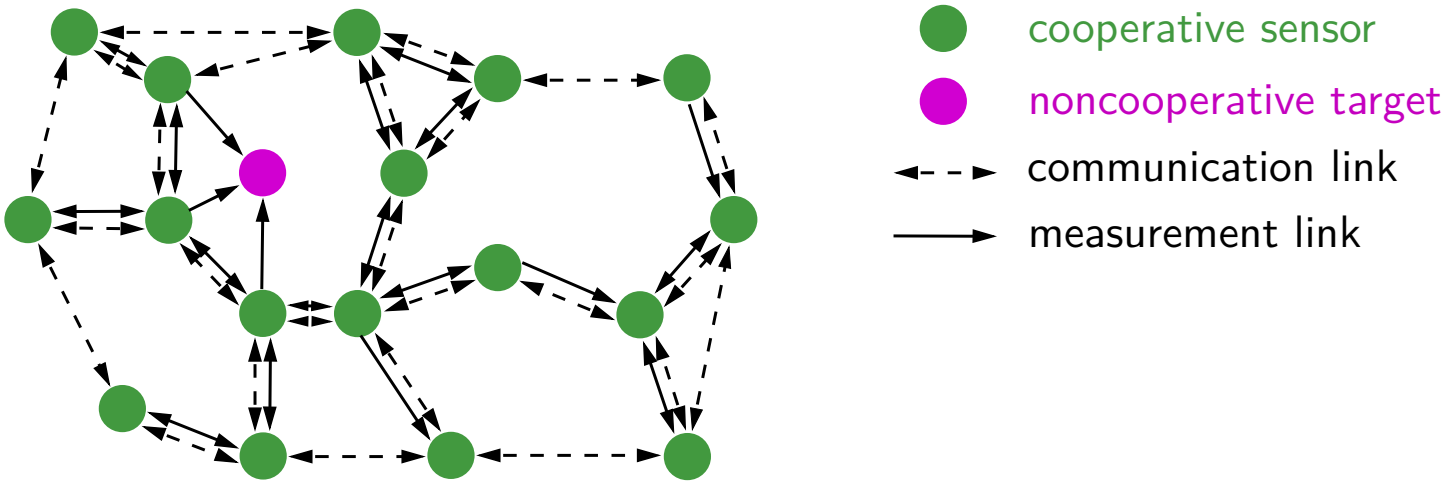

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- The state $\mathbf{x}_{k,n}$ of sensor or target k at time n consists of the current position and, possibly, other local parameters such as the current velocity

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Factorization of Joint Posterior

- Joint CSL and DTT: All sensors k estimate their own state $\mathbf{x}_{k,n}$ and the target state $\mathbf{x}_{0,n}$ in a distributed manner using pairwise measurements of the distance $y_{k,l;n}$

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- The joint posterior pdf for the combined CSL–DTT problem can be expressed/factored as

$$f(\mathcal{X}_{0:n}|\mathcal{Y}_{1:n}) \propto \left[\prod_{k=0}^{K} f(\mathbf{x}_{k,0})\right] \prod_{n'=1}^{n} \left[\prod_{k'=0}^{K} f(\mathbf{x}_{k',n'}|\mathbf{x}_{k',n'-1}) \prod_{l \in \mathcal{M}_{k',n'}} f(y_{k',l;n'}|\mathbf{x}_{k',n'}, \mathbf{x}_{l,n'})\right] \quad (1)$$

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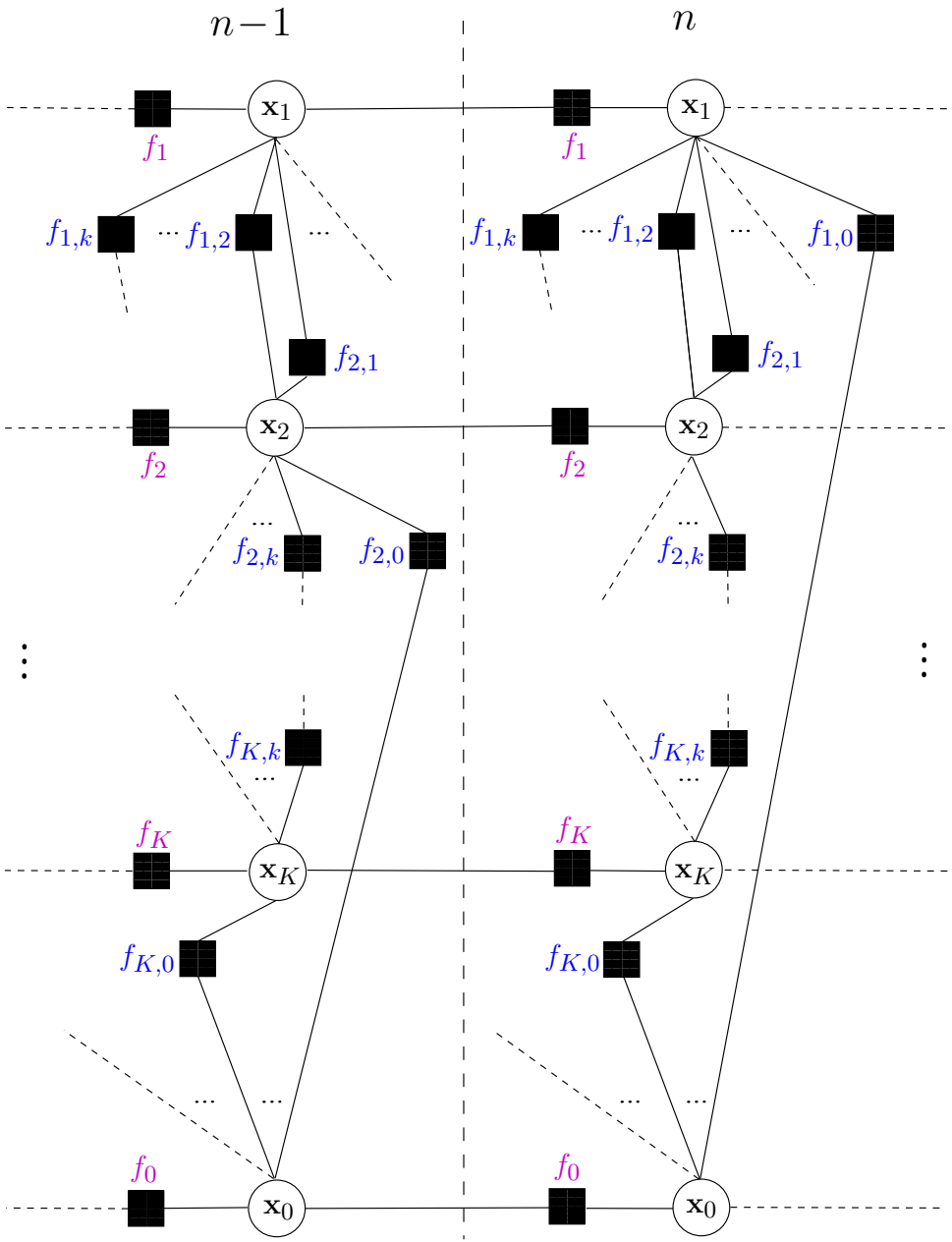
- However, the marginal posterior $f(\mathbf{x}_{k,n}|\mathcal{Y}_{1:n})$ is needed for estimating $\mathbf{x}_{k,n}$!

- To marginalize $f(\mathcal{X}_{0:n}|\mathcal{Y}_{1:n})$, we use a belief propagation algorithm, based on a factor graph expressing the factorization in (1)

Factor Graph



- Two consecutive time steps $n-1$, n are shown
- $f_{k,l}$ is short for $f(y_{k,l;n'}|\mathbf{x}_{k,n'}, \mathbf{x}_{l,n'})$, $n' \in \{1, \ldots, n\}$
- f_k is short for $f(\mathbf{x}_{k,n'}|\mathbf{x}_{k,n'-1})$, $n' \in \{1, \ldots, n\}$

Belief Propagation Message Passing Scheme

- Based on this factor graph, the marginal posteriors $f(\mathbf{x}_{k,n}|\mathcal{Y}_{1:n})$ can be computed by means of an iterative belief propagation algorithm

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- The approximate marginal posterior ("belief") of agent k at time n and message passing iteration $p \in \{1, \ldots, P\}$, $b_{k,n}^{(p)}(\mathbf{x}_{k,n}) \approx f(\mathbf{x}_{k,n}|\mathcal{Y}_{1:n})$, can be calculated as [Wymeersch et al., 2009]

$$b_{k,n}^{(p)}(\mathbf{x}_{k,n}) \propto \begin{cases} m_{\to n}(\mathbf{x}_{k,n}) \prod\limits_{l \in \mathcal{M}_{k,n}} m_{l \to k}^{(p)}(\mathbf{x}_{k,n}) \,, & k \neq 0 \\ m_{\to n}(\mathbf{x}_{0,n}) \prod\limits_{l \in \mathcal{T}_n} m_{l \to 0}^{(p)}(\mathbf{x}_{0,n}) \,, & k = 0 \end{cases}$$

with the messages

$$m_{\to n}(\mathbf{x}_{k,n}) \triangleq \int f(\mathbf{x}_{k,n}|\mathbf{x}_{k,n-1})\, b_{k,n-1}^{(P)}(\mathbf{x}_{k,n-1})\, d\mathbf{x}_{k,n-1}$$

$$m_{l \to k}^{(p)}(\mathbf{x}_{k,n}) \triangleq \int f(y_{k,l;n}|\mathbf{x}_{k,n}, \mathbf{x}_{l,n})\, b_{l,n}^{(p-1)}(\mathbf{x}_{l,n})\, d\mathbf{x}_{l,n}$$

[Wymeersch et al., 2009] H. Wymeersch, J. Lien, and M. Z. Win, "Cooperative localization in wireless networks," Proc. IEEE, 2009.

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Hybrid Particle-based/Parametric Belief Propagation

- In the CoSLAT algorithm proposed in [Meyer et al., 2012], beliefs and messages are represented by particles $\{\mathbf{x}^{(j)}\}_{j=1}^{J}$ and weights $\{w^{(j)}\}_{j=1}^{J}$. This algorithm has complexity $\mathcal{O}(J^2)$

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- Here, we propose an advanced "hybrid" CoSLAT algorithm that uses a Gaussian parametric representation of the beliefs and an annular parametric representation of certain messages

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- Here, we propose an advanced "hybrid" CoSLAT algorithm that uses a Gaussian parametric representation of the beliefs and an annular parametric representation of certain messages
- In this way, the complexity is reduced from $\mathcal{O}(J^2)$ to $\mathcal{O}(J)$ and the communication cost is reduced by an order of magnitude

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Parametric Representation of Beliefs

- If the belief $b_{l,n}^{(p-1)}(\mathbf{x}_{l,n})$ is unimodal, we represent it by a Gaussian $\mathcal{N}(\boldsymbol{\mu}_{l,n}, \mathbf{C}_{l,n})$

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- If $b_{l,n}^{(p-1)}(\mathbf{x}_{l,n})$ is bimodal, we represent it by a mixture of two Gaussians $\mathcal{N}(\boldsymbol{\mu}_{l,n}^{(1)}, \mathbf{C}_{l,n}^{(1)})$ and $\mathcal{N}(\boldsymbol{\mu}_{l,n}^{(2)}, \mathbf{C}_{l,n}^{(2)})$ with equal weights

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- If $b_{l,n}^{(p-1)}(\mathbf{x}_{l,n})$ is multimodal, no belief parameters are transmitted, because a poorly localized node cannot provide information to its partners

Parametric Representation of Messages

- If $b_{l,n}^{(p-1)}(\mathbf{x}_{l,n})$ is unimodal, we represent the message $m_{l\to k}^{(p)}(\mathbf{x}_{k,n})$ by an annulus about $\boldsymbol{\mu}_{l,n}$

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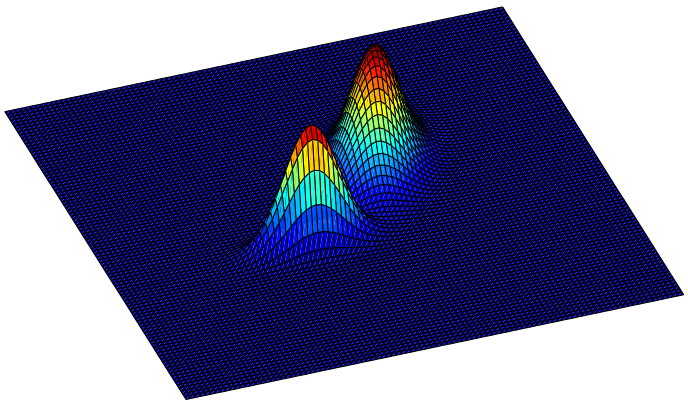
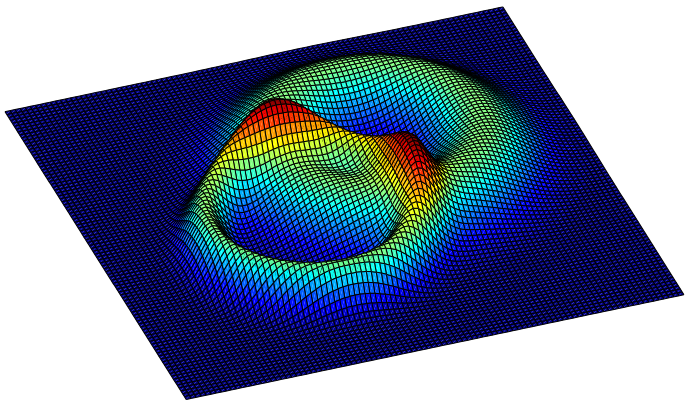
- If $b_{l,n}^{(p-1)}(\mathbf{x}_{l,n})$ is multimodal, we set $m_{l\to k}^{(p)}(\mathbf{x}_{k,n})$ to a constant value (i.e., node k ignores localization partner l)

Particle Representation of Messages

- Example of a bimodal Gaussian belief $b_{l,n}^{(p-1)}(\mathbf{x}_{l,n})$ (left) and the corresponding bi-annular message $m_{l\to k}^{(p)}(\mathbf{x}_{k,n})$ (right):





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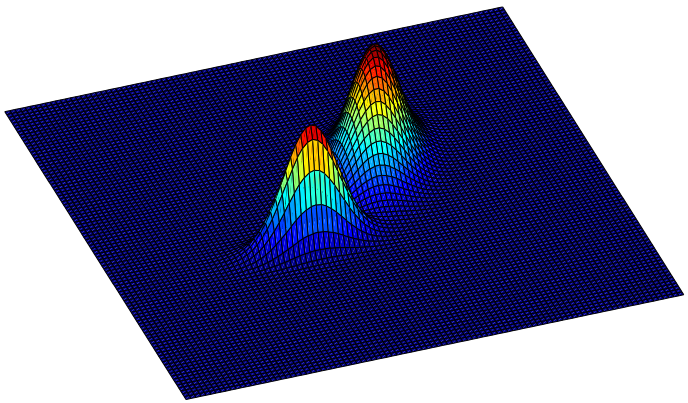

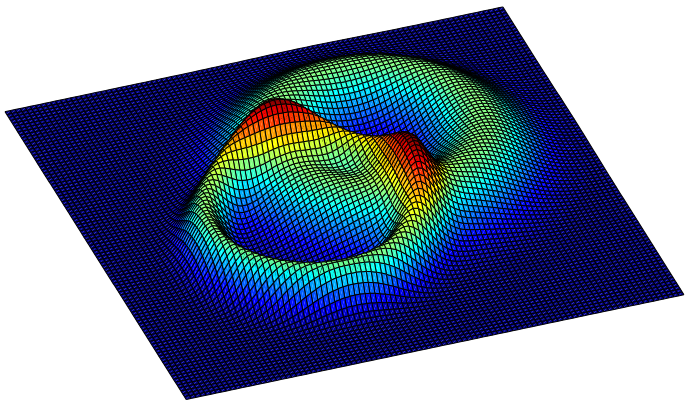

- With all messages $m_{l\to k}^{(p)}(\mathbf{x}_{k,n})$ locally available, node k obtains a particle representation of $b_{k,n}^{(p)}(\mathbf{x}_{k,n})$ by performing importance sampling; this has complexity $\mathcal{O}(J)$

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Likelihood Consensus

- With CoSLAT, differently from pure CSL, a distributed implementation of the belief propagation message passing scheme is complicated by the fact that the target node is noncooperative

- More specifically, for calculating the approximate marginal posterior of the target state, $b_{0,n}^{(p)}(\mathbf{x}_{0,n})$, the message product $\prod_{l \in \mathcal{T}_n} m_{l \to 0}^{(p)}(\mathbf{x}_{0,n})$ is required – unfortunately, it is not available at the sensors

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- We solve this problem by using the likelihood consensus scheme [Hlinka et al., 2012]

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- Thus, each sensor k is able to calculate the approximate marginal of its own state $\mathbf{x}_{k,n}$ and of the target state $\mathbf{x}_{0,n}$, based on information that is either locally available or obtained through local communication

[Hlinka et al., 2012] O. Hlinka, O. Sluciak, F. Hlawatsch, P.M. Djuric, and M. Rupp, "Likelihood consensus and its application to distributed particle filtering,", IEEE Trans. Signal Processing, 2012

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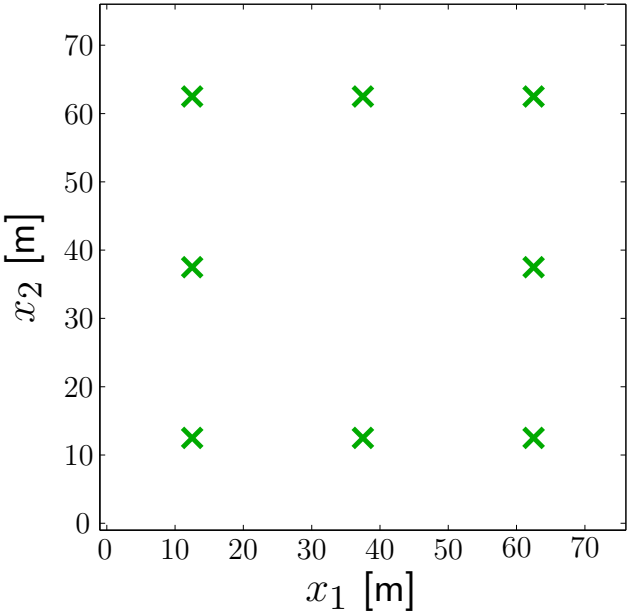

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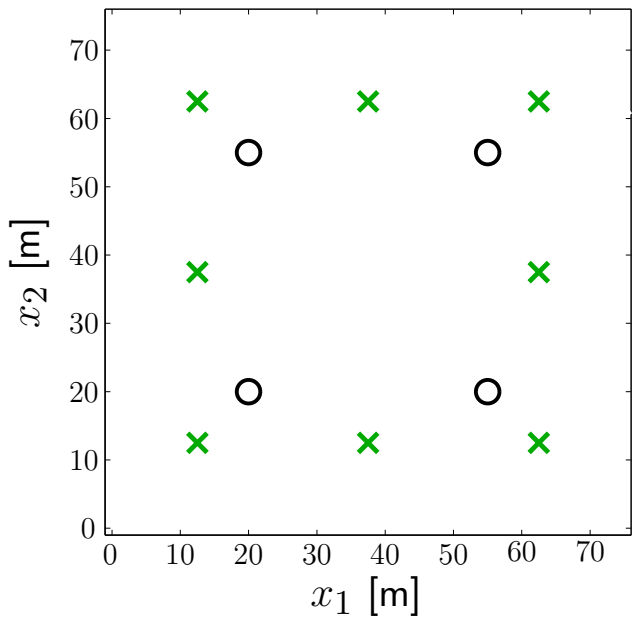

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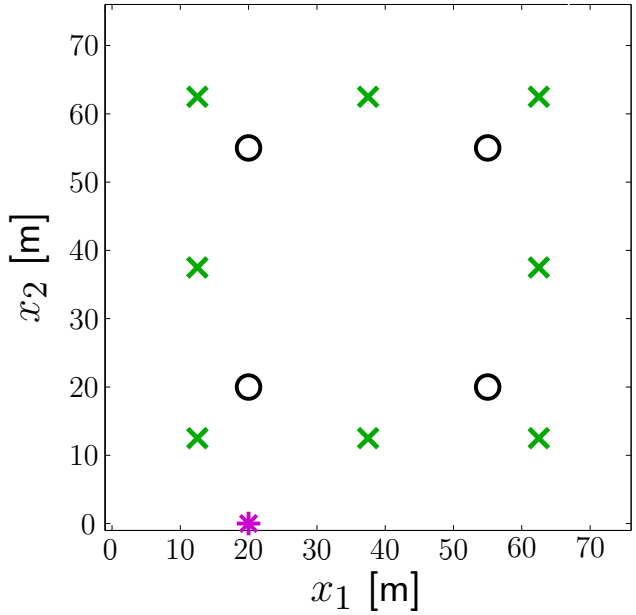

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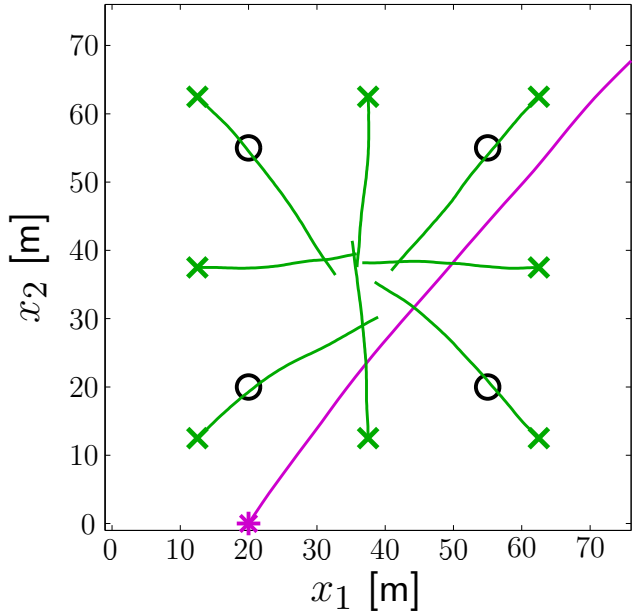

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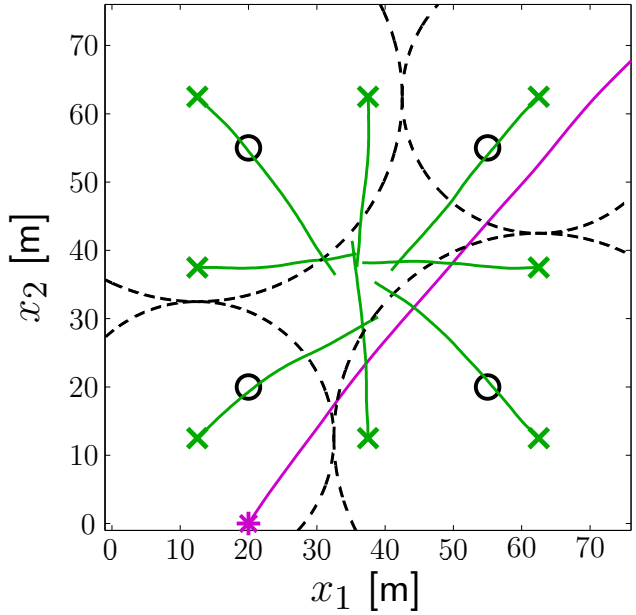

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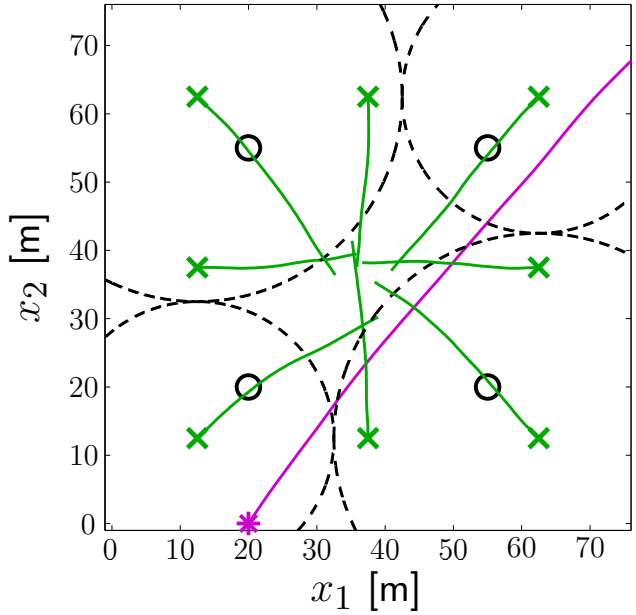

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- The communication range of all sensors is 50m

Simulation Setup

- We compare the following methods:
  1. The proposed hybrid CoSLAT algorithm
  2. The original particle-based CoSLAT algorithm [Meyer et al., 2012]
  3. A state-of-the-art method that performs separate CSL (using nonparametric belief propagation [Lien et al., 2012]) and DTT (using a likelihood consensus based distributed particle filter [Hlinka et al., 2012])

[Meyer et al., 2012] F. Meyer, E. Riegler, O. Hlinka, and F. Hlawatsch, "Simultaneous distributed sensor self-localization and target tracking using belief propagation and likelihood consensus," in Proc. 46th Asilomar Conf., 2012

[Lien et al., 2012] J. Lien, J. Ferner, W. Srichavengsup, H. Wymeersch, and M. Z. Win, "A comparison of parametric and sample-based message representation in cooperative localization," Int. J. Navig. Observ., 2012

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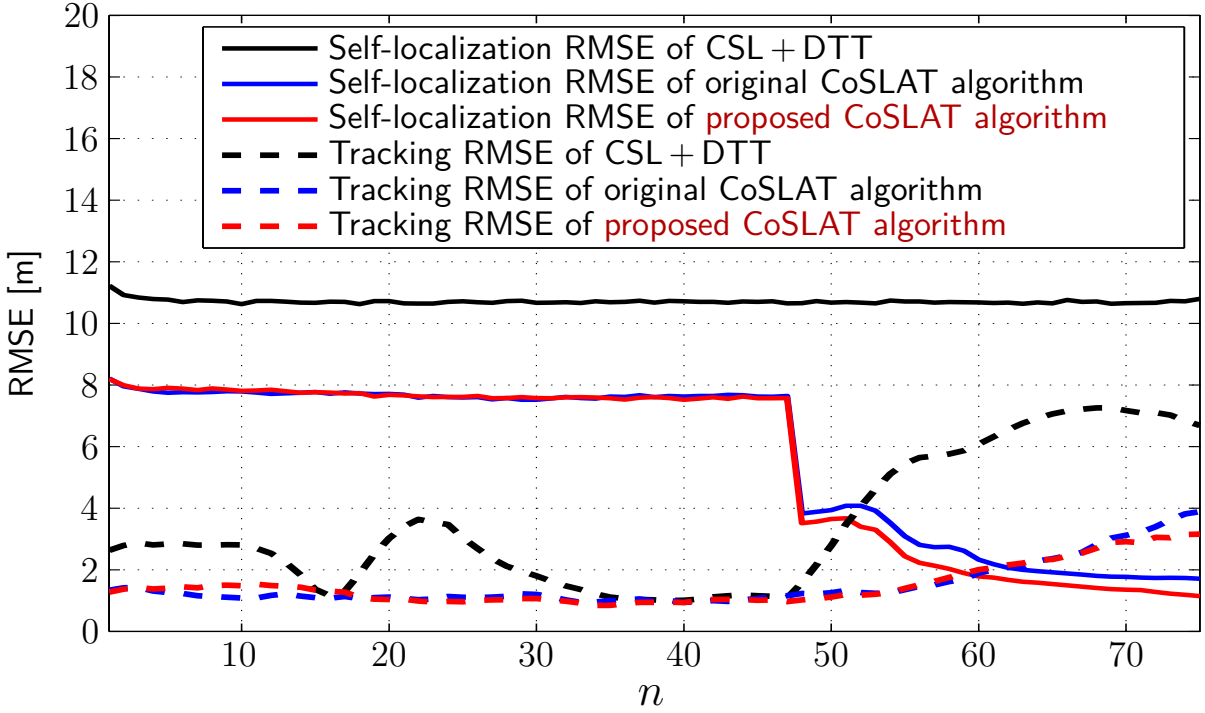
Simulation Results

- Root mean-square error (RMSE) versus time n:



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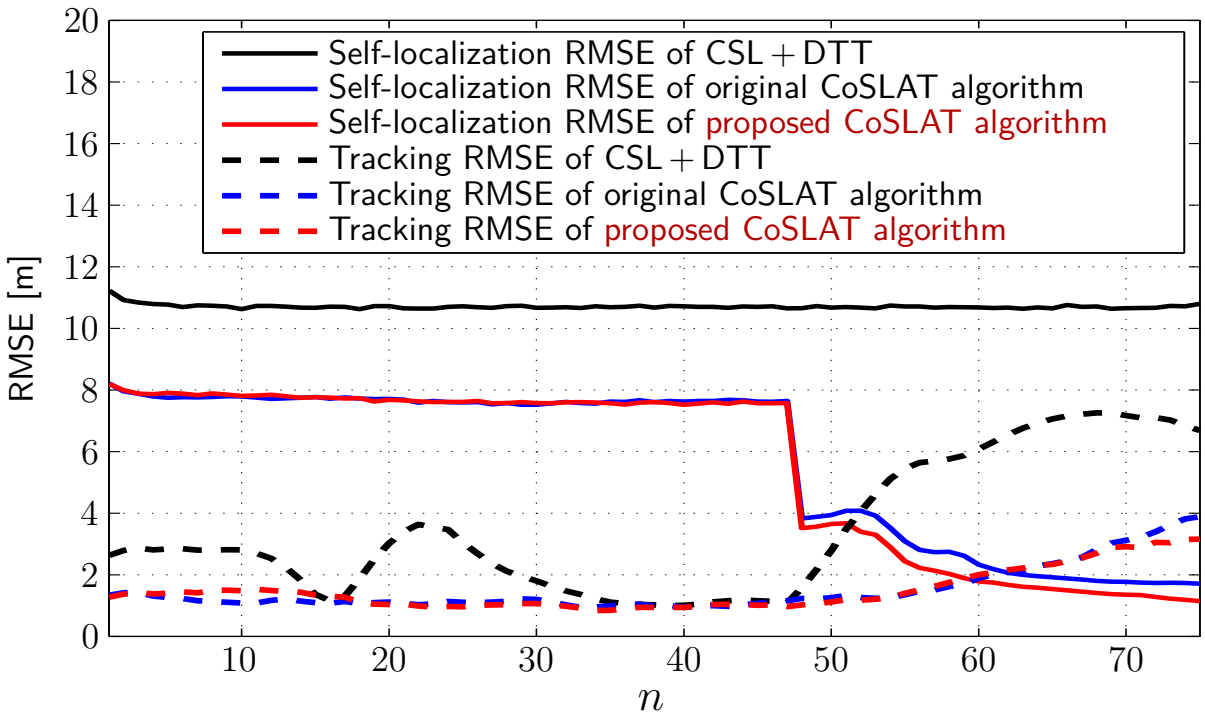

- Despite achieving an substantial reduction of communication and complexity, the proposed CoSLAT algorithm exhibits no loss in performance compared to the original CoSLAT algorithm

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- Compared to an exisiting CoSLAT algorithm, the proposed algorithm achieves a substantial reduction of communications and computations, with no loss in performance

Thank you!