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

Florian Meyer\textsuperscript{1}, Franz Hlawatsch\textsuperscript{1}, and Henk Wymeersch\textsuperscript{2}

\textsuperscript{1}Institute of Telecommunications, Vienna University of Technology, Austria
\textsuperscript{2}Department of Signals and Systems, Chalmers University of Technology, Gothenburg, Sweden
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].

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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• Message Passing Scheme
• Hybrid Particle-based/Parametric Belief Propagation
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• Simulation Results
• Conclusion
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Sensors and target may be mobile $\Rightarrow$ the communication and measurement topologies may be time-varying.

The state $x_{k,n}$ 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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Joint CSL and DTT: All sensors $k$ estimate their own state $x_{k,n}$ and the target state $x_{0,n}$ in a distributed manner using pairwise measurements of the distance $y_{k,l;n}$.
Factorization of Joint Posterior

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

$$f(X_0:n|Y_{1:n}) \propto \left[ \prod_{k=0}^{K} f(x_{k,0}) \right] \prod_{n'=1}^{n} \left[ \prod_{k'=0}^{K} f(x_{k',n'}|x_{k',n'-1}) \prod_{l \in M_{k',n'}} f(y_{k',l;n'}|x_{k',n'},x_{l,n'}) \right]$$

(1)
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- However, the marginal posterior $f(x_{k,n}|Y_1:n)$ is needed for estimating $x_{k,n}$!

- To marginalize $f(X_0:n|Y_1:n)$, we use a belief propagation algorithm, based on a factor graph expressing the factorization in (1)
Two consecutive time steps $n-1, n$ are shown

$f_{k,l}$ is short for $f(y_{k,l}; n' | x_{k,n'}, x_{l,n'})$, $n' \in \{1, \ldots, n\}$

$f_{k}$ is short for $f(x_{k,n'} | x_{k,n'-1})$, $n' \in \{1, \ldots, n\}$
Belief Propagation Message Passing Scheme

- Based on this factor graph, the marginal posteriors $f(x_{k,n}|Y_{1:n})$ 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 $p \in \{1, \ldots, P\}$, $b^{(p)}_{k,n}(x_{k,n}) \approx f(x_{k,n}|Y_{1:n})$, can be calculated as [Wymeersch et al., 2009]

$$b^{(p)}_{k,n}(x_{k,n}) \propto \begin{cases} m_{\rightarrow n}(x_{k,n}) \prod_{l \in M_{k,n}} m^{(p)}_{l \rightarrow k}(x_{k,n}), & k \neq 0 \\ m_{\rightarrow n}(x_{0,n}) \prod_{l \in T_{n}} m^{(p)}_{l \rightarrow 0}(x_{0,n}), & k = 0 \end{cases}$$

with the messages

$$m_{\rightarrow n}(x_{k,n}) \triangleq \int f(x_{k,n}|x_{k,n-1}) b^{(P)}_{k,n-1}(x_{k,n-1}) \, dx_{k,n-1}$$

$$m^{(p)}_{l \rightarrow k}(x_{k,n}) \triangleq \int f(y_{k,l;n}|x_{k,n}, x_{l,n}) b^{(p-1)}_{l,n}(x_{l,n}) \, dx_{l,n}$$

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

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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.

• If the belief $b_{l,n}^{(p-1)}(x_{l,n})$ is unimodal, we represent it by a Gaussian $\mathcal{N}(\mu_{l,n}, C_{l,n})$.
Parametric Representation of Beliefs

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- If $b_{l,n}^{(p-1)}(x_{l,n})$ is multimodal, no belief parameters are transmitted, because a poorly localized node cannot provide information to its partners
If $b_{l,n}^{(p-1)}(x_{l,n})$ is unimodal, we represent the message $m_{l \rightarrow k}^{(p)}(x_{k,n})$ by an annulus about $\mu_{l,n}$.
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Parametric Representation of Messages

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- If $b_{l,n}^{(p-1)}(x_{l,n})$ is bimodal, we represent $m_{l\rightarrow k}^{(p)}(x_{k,n})$ by the sum of two annuli

- If $b_{l,n}^{(p-1)}(x_{l,n})$ is multimodal, we set $m_{l\rightarrow k}^{(p)}(x_{k,n})$ to a constant value (i.e., node $k$ ignores localization partner $l$)
Example of a bimodal Gaussian belief $b^{(p-1)}_{l,n}(x_{l,n})$ (left) and the corresponding bi-annular message $m^{(p)}_{l \rightarrow k}(x_{k,n})$ (right):
Example of a bimodal Gaussian belief $b_{l,n}^{(p-1)}(x_{l,n})$ (left) and the corresponding bi-annular message $m_{l \rightarrow k}^{(p)}(x_{k,n})$ (right):

With all messages $m_{l \rightarrow k}^{(p)}(x_{k,n})$ locally available, node $k$ obtains a particle representation of $b_{k,n}^{(p)}(x_{k,n})$ by performing importance sampling; this has complexity $O(J)$.
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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, $b_{0,n}^{(p)}(x_0,n)$, the message product $\prod_{l \in \mathcal{T}_n} m_{l \rightarrow 0}^{(p)}(x_0,n)$ is required – unfortunately, it is not available at the sensors.
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- Thus, each sensor $k$ is able to calculate the approximate marginal of its own state $x_{k,n}$ and of the target state $x_{0,n}$, based on information that is either locally available or obtained through local communication.

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Sensor Network Topology

- Eight mobile sensors (initial positions are indicated by ×)
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• **Four anchor sensors** (static sensors with perfect position information; positions are indicated by o)
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- **One mobile target** (initial position is indicated by ∗)
- Eight mobile sensors (initial positions are indicated by ×)

- Four anchor sensors (static sensors with perfect position information; positions are indicated by o)

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Sensor Network Topology

- **Eight mobile sensors** (initial positions are indicated by ×)
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- The **measurement regions** of the four sensors in the corners are indicated by big dashed circles; the measurement regions of the other sensors cover the entire field
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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])**


Simulation Results

- Root mean-square error (RMSE) versus time $n$:
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![Root mean-square error (RMSE) versus time $n$.]

- 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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We proposed a hybrid CoSLAT algorithm that uses belief propagation with parametric and particle-based representations of beliefs messages.

Compared to an existing CoSLAT algorithm, the proposed algorithm achieves a substantial reduction of communications and computations, with no loss in performance.
Thank you!