

Target aided online sensor localisation in bearing only clusters

Murat Üney¹, Bernard Mulgrew¹, Daniel Clark²

Edinburgh Research Partnership in Signal and Image Processing

¹ *The University of Edinburgh*

² *Heriot-Watt University*

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Introduction

- Bearing-only sensors detect objects and record their line-of-sight (LOS) angles, in their sensor coordinate systems.
- Fusion clusters filter target detections.
- Sensor locations are needed for fusion and routing.
- GPS denying environments, jamming,...
- Target detections and Received Signal Strength (RSS) at the communication front-end are used.

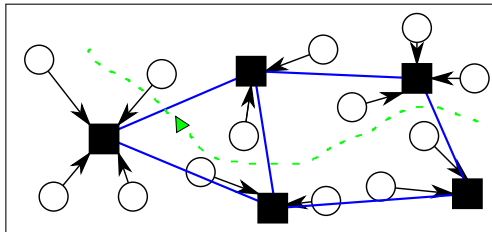
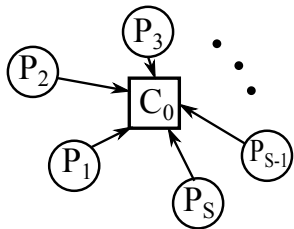


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Problem Definition

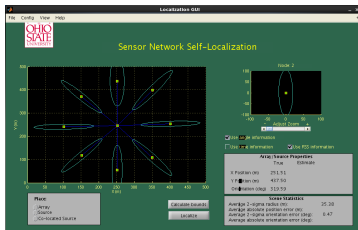


The cluster head C_0

- 1 collects target detections $Z_{1:T}^0$ in a time window of T with its on-board bearing only sensor,
 - 2 receives $Z_{1:T}^i$ from peripheral P_i .
 - 3 The i^{th} comm.s signal arrives at the receiver with power R^i (or Received Signal Strength-RSS).
- Find locations $\theta \triangleq [\theta_1, \theta_2, \dots, \theta_S]$ given $Z_{1:T}^0, Z_{1:T}^1, \dots, Z_{1:T}^S$ and R_1, \dots, R_S .
 - The uncertainties are captured within $l(Z_{1:T}^0, Z_{1:T}^1, \dots, Z_{1:T}^S | \theta)$, and, $l(R^1, \dots, R^S | \theta)$.

Conventional Approaches (1/3)

- Cramer-Rao Lower Bounds for $I(R^1, \dots, R^S | \theta) = \prod I(R^i | \theta_i)$:



- High uncertainty because that $I(R^i | d^i = |\theta_i|)$ is log-normal resulting with a wide distribution.

Conventional Approaches (2/3)

- Target detections based likelihood is given by

$$\begin{aligned} l(Z_{1:T}^0, Z_{1:T}^1, \dots, Z_{1:T}^S | \theta) &= \prod_{t=0}^{T-1} p(Z_{t+1}^{0:S} | Z_{1:t-1}^{0:S}, \theta) \\ &= \prod_{t=0}^{T-1} \int p(Z_{t+1}^0 | X_{t+1}) \prod_{i=1}^S p(Z_{t+1}^i | X_{t+1}, \theta_i) \\ &\quad \times \underbrace{p(X_{t+1} | Z_{1:T}^0, Z_{1:T}^1, \dots, Z_{1:T}^S, \theta)}_{\text{Prediction distribution of a (centralised) filter.}} d(X^{t+1}) \end{aligned}$$

- Intractable, in general. Monte Carlo (MC) approx. needed.
- Increasing MC variance as the time window length T grows larger \sim particle deficiency (Kantas, Doucet, et.al., 2010).

Conventional Approaches (3/3)

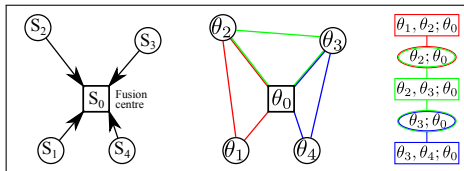
- Bayesian recursions for an online solution:

$$p_n(\theta_n) \propto l(Z_{T(n-1)+1:T_n}^{0:S} | \theta_n) p_{n|n-1}(\theta_n)$$
$$p_{n|n-1}(\theta_n) = \int f_n(\theta_n | \theta_{n-1}) p_{n-1}(\theta_{n-1}) d\theta_{n-1}$$

- Scalability of the update with the # of sensors S (equivalently, the dimensionality of θ):
 - Update is $\mathcal{O}((S^{\alpha+1}N)(ST)M)$.
 - N : The number of particles per sensor,
 - M : The number of progressive Importance Sampling (or, stochastic tempering) stages.
- With given N , M , and, the sophistication of the samplers, might fail to converge.

Proposed Solution (1/2)

- Divide the problem into simpler subproblems and merge their solutions.
- Use a Junction Tree (equivalently, a triangulated Markov Random Field) model for the localisation posterior:



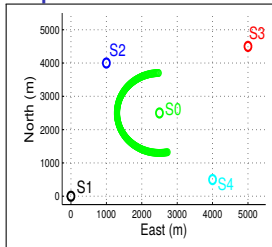
$$p(\theta) \propto \frac{\prod_{k=1}^{S-1} l(Z^0, Z^{i_k}, Z^{i_{k+1}} | \theta_{i_k}, \theta_{i_{k+1}})}{\prod_{k=2}^{S-1} l(Z^0, Z^{i_k} | \theta_{i_k})} \prod_{i=1}^S p_{0,i}(\theta_i).$$

Pairwise MRF models for self-localisation of range-bearing sensors (Uney, Mulgrew, Clark, "Cooperative sensor localisation for distributed fusion networks").

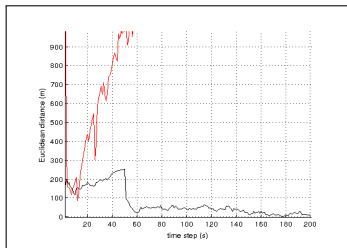
Proposed Solution (2/2)

- Update one marginal of $p_n(\theta_n)$ at a time using the Junction Tree message passing algorithm: The Importance Sampling scheme is detailed in the article.
- $\mathcal{O}(N(3T)S^{\beta+1})$ (as opposed to $\mathcal{O}((S^{\alpha+1}N)(ST)M)$) with typically much smaller N .
- Convergence properties are improved by the introduction of RSS likelihoods $l(R^i|\theta_i)$ s to shape priors.

Example



- LOS angle standard deviation $\sigma_i = 0.5^\circ$.
- $T = 10$ step window-length, $N = 150$ particles per sensor.
- Final error (averaged over sensors) is 45.7m (%2.15 of the nearest peripheral distance (2121.3m of sensor 2)).



- Tracking error (Euclidean distance) of the cluster (black) when location estimates are used (in comparison with cluster-head only (red) tracking).

Conclusions and Future Work

- We considered sensor localisation in bearing only sensor clusters for target filtering and routing.
- Our solution uses target detections and RSS measurements.
- Scales well with the number of sensors.
- Further empirical study of clutter effects using Bernoulli filters.
- Further empirical comparison of the accuracy and complexity of progressive Importance Sampling schemes and the proposed solution.



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