On the Particle-Assisted Stochastic Search In Cooperative Wireless Network Localization

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3 Algorithm Design

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Introduction

Motivation and Problem Formulation

Challenges

Due to nonlinear measurement function and reference node location errors,

- the objective function is non-convex;
- there is no closed-form expression of the objective function;
- reference node location error should be considered to reap more performance.

$$p(\mathbf{s}_i|\mathbf{z}_i) \propto \mathcal{N}(\mathbf{s}_i|\boldsymbol{\mu}_i, \mathbf{U}_i) \prod_{j\in\Psi_i} \int \frac{|\mathrm{w}_{i,j}|^{\frac{1}{2}}}{\sqrt{2\pi}} \exp\left(-\frac{1}{2}\mathrm{w}_{i,j}\left(\mathrm{z}_{i,j} - h(\mathbf{s}_i, \mathbf{s}_j)\right)^2\right) \mathcal{N}(\mathbf{s}_j|\boldsymbol{\mu}_j, \mathbf{U}_j)\,\mathrm{d}\mathbf{s}_j.$$

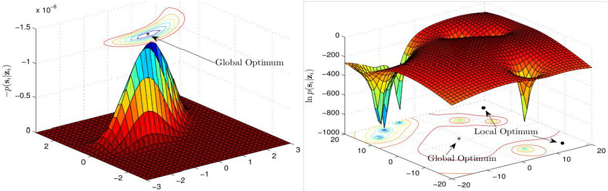

Figure: A specific example of $-p(\mathbf{s}_i|\mathbf{z}_i)$ and $\ln p(\mathbf{s}_i|\mathbf{z}_i)$ in cooperative localization.

Introduction

Motivation and Problem Formulation

Solutions → drawbacks

- Importance sampling-based positioning method → limited particle efficiency when the priori is quite different from likelihood.
- Taylor expansion-based approximation → reference node location error.
- Optimization relaxation → the solution may be beyond original feasible set.
- Sigma point-based approximation → non-convex optimization issue remains.
- Stochastic particle-based optimization method (main concern) → exploration capability and intractable objective function.

Stochastic particle-based optimization method

- Exploration capability should be improved further, particularly when the global optimum is out of the initial particle coverage.
- Complicated objective function calculation should be resolved.
- Reference node location errors should be considered.

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System Model

Network Model

A static wireless network is considered, where

- a total of M nodes are assumed;
- all network node initial locations are inaccurate, $\mathbf{s}_i \sim \mathcal{N}(\mathbf{s}_i | \boldsymbol{\mu}_i, \mathbf{U}_i)$, $\forall i = 1 : M$;
- sensing range is r_s;
- reference cluster set of $\mathbf{s}_i$ is defined as $\Psi_i \doteq \{j : \|\mathbf{s}_j - \mathbf{s}_i\|_2 < r_s, \forall j \neq i\}$.

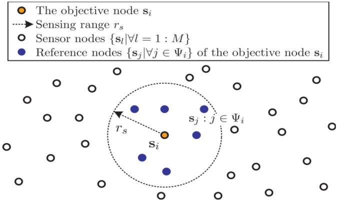

Figure: Illustration of the network node deployment.

System Model

Measurement Model

The measurement data $\mathrm{z}_{i,j}$ from $\mathbf{s}_j$ to $\mathbf{s}_i$ is modeled as

$$\mathrm{z}_{i,j} = h(\mathbf{s}_i, \mathbf{s}_j) + \epsilon_{i,j}, \ \forall j \in \Psi_i \text{ and } \forall i = 1 : M, \tag{1}$$

where $\epsilon_{i,j} \sim \mathcal{N}\left(\epsilon_{i,j} \,|\, 0, \mathrm{w}_{i,j}\right)$ denotes the measurement noise and $h(\mathbf{s}_i, \mathbf{s}_j)$ stands for the measurement function (possibly nonlinear).

Problem Formulation

Given the coarse locations and their precisions $\{\boldsymbol{\mu}_i, \mathbf{U}_i | \forall i = 1 : M\}$ of all network nodes and the measurements $\{\mathrm{z}_{i,j} | \forall j \in \Psi_i, \forall i = 1 : M\}$ among these nodes, how to determine all node locations.

System Model

Statistical Model

The objective function associated with the cooperative localization is

$$p(\mathbf{s}_i|\mathbf{z}_i) \propto \mathcal{N}(\mathbf{s}_i|\boldsymbol{\mu}_i, \mathbf{U}_i) \prod_{j\in\Psi_i} \int \frac{|\mathrm{w}_{i,j}|^{\frac{1}{2}}}{\sqrt{2\pi}} \exp\left(-\frac{1}{2}\mathrm{w}_{i,j}\left(\mathrm{z}_{i,j} - h(\mathbf{s}_i, \mathbf{s}_j)\right)^2\right) \mathcal{N}(\mathbf{s}_j|\boldsymbol{\mu}_j, \mathbf{U}_j)\, \mathrm{d}\mathbf{s}_j, \quad (2)$$

which is non-convex and intractable.

In order to facilitate analysis, we use a general function $f(\mathbf{x})$ to represent the logarithm of posteriori, *i.e.*, $\ln p(\mathbf{s}_i|\mathbf{z}_i)$, where we suppose $\mathbf{x}$ denote the target node location $\mathbf{s}_i$.

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Algorithm Design

A particle-assisted stochastic search (PASS) method

A set of stochastic search particles $\{\mathbf{x}_k(m) \,|\forall m = 1 : N_\mathrm{S}\}$ are used in PASS to incorporate both local and global information in search stage.

Search Particle Generation

The initial search particles (when $k = 1$) can be generated from the priori distribution,

$$\{\mathbf{x}_1(m) \,|\forall m = 1 : N_\mathrm{S}\} \sim p(\mathbf{x}), \tag{3}$$

or be uniformly generated inside the feasible area when there is no priori information.

Search Particle Update

Given the current stochastic search particle set $\{\mathbf{x}_k(m) \,|\forall m = 1 : N_\mathrm{S}\}$, each search particle $\mathbf{x}_k(m)$ updates (by combining both the local and global information) as below

$$\mathbf{x}_{k+1}(m) = \mathbf{x}_k(m) + \gamma_1 \mathbf{y}_k(m) + \gamma_2 \mathbf{s}_k^\star, \ \forall m = 1 : N_\mathrm{S}, \tag{4}$$

such that $f(\mathbf{x}_{k+1}(m)) \geq f(\mathbf{x}_k(m))$ with a high probability, where $\mathbf{y}_k(m)$ stands for the local best update vector, while $\mathbf{s}_k^\star$ denotes the global best update vector. In addition, γ_1 and γ_2 denote nonnegative update lengths and $0 < \gamma_1 + \gamma_2 \leq 1$.

Algorithm Design

The proposed PASS algorithm framework

Global Best Search

In Eq. (4), the current global best update vector $\mathbf{s}_k^\star$ is defined as

$$\mathbf{s}_k^\star = \mathbf{r}_k^\star - \mathbf{x}_k(m), \tag{5}$$

$$\mathbf{r}_k^\star = \arg\max_{\mathbf{x}_k(m)} \left\{ \varphi_k(m) \,|\forall m = 1 : N_{\mathrm{S}} \right\}, \tag{6}$$

where $\varphi_k(m)$ stands for the associated belief of the mth search particle $\mathbf{x}_k(m)$.

Global Best Search - Importance Sampling

Hence, the belief $\varphi_k(m)$ is calculated with a local smooth as

$$\varphi_k(m) = \int \ell\left(\tilde{\mathbf{x}}_k(m)|\mathbf{x}_k(m)\right) f\left(\tilde{\mathbf{x}}_k(m)\right) \mathrm{d}\tilde{\mathbf{x}}_k(m) \approx \sum_{n=1:N_{\mathrm{M}}} \omega_k(m;n) f\left(\mathbf{x}_k(m;n)\right), \tag{7}$$

where $\left\{\mathbf{x}_k(m;n), \omega_k(m;n) \,|\forall n = 1 : N_{\mathrm{M}}\right\}$ denotes the importance sampling particle set of $\mathbf{x}_k(m)$, which is drawn from the proposal density $\ell\left(\tilde{\mathbf{x}}_k(m)|\mathbf{x}_k(m)\right) = \mathcal{N}\left(\tilde{\mathbf{x}}_k(m)|\mathbf{x}_k(m), \boldsymbol{\Theta}\right)$, with precision $\boldsymbol{\Theta}$. N_{M} stands for the set size, and $f\left(\mathbf{x}_k(m;n)\right)$ will be given in (15).

Algorithm Design

The proposed PASS algorithm framework

Local Best Detection

The current local best update vector $\mathbf{y}_k(m)$ is defined as[a]

$$\mathbf{y}_k(m) = \mathbf{x}_k^\star(m) - \mathbf{x}_k(m), \tag{8}$$

$$\mathbf{x}_k^\star(m) = \arg \max_{\mathbf{x}_k^{(\tau)}(m)} \left\{ \varsigma_k^{(\tau)}(m) \,|\forall \tau = 1 : N_{\mathrm{D}} \right\}, \tag{9}$$

where $\left\{ \mathbf{x}_k^{(\tau)}(m), \varsigma_k^{(\tau)}(m) \,|\forall \tau = 1 : N_{\mathrm{D}} \right\}$ stands for the detection particle set of search particle $\mathbf{x}_k(m)$, and N_{D} stands for the detection particle set size. $\varsigma_k^{(\tau)}(m)$ stands for the belief of the τth detection particle $\mathbf{x}_k^{(\tau)}(m)$ of the mth search particle $\mathbf{x}_k(m)$,

$$\mathbf{x}_k^{(\tau)}(m) = \mathbf{x}_k(m) + \boldsymbol{\upsilon}_k^{(\tau)}(m), \tag{10}$$

$$\varsigma_k^{(\tau)}(m) \approx \sum_{n=1:N_{\mathrm{M}}} \omega_k^{(\tau)}(m;n) f\left(\mathbf{x}_k^{(\tau)}(m;n)\right), \tag{11}$$

[a] Here, $\mathbf{x}_k^\star(m)$ stands for the best location in the local detection area near the current search particle $\mathbf{x}_k(m)$. This novel local detection enable the proposed PASS algorithm explore new space that the global optimum possibly exists in. This mechanism will enhance the associated search capability, particularly when the global optimum is out of the initial coverage of the search particles

Algorithm Design

The proposed PASS algorithm framework

Local Best Detection

The stochastic detection vector $\upsilon_k^{(\tau)}(m)$ in Eq. (10) is given by

$$\upsilon_k^{(\tau)}(m) = L \begin{bmatrix} \cos\left(\theta_k^{(\tau)}(m)\right) \\ \sin\left(\theta_k^{(\tau)}(m)\right) \end{bmatrix} \text{ and } \theta_k^{(\tau)}(m) \sim \mathrm{rand}(0, 2\pi), \tag{12}$$

where L stands for the detection step length (considering a 2-dimensional case).

Location Estimation

At each search step, $\mathbf{x}_k$ can be determined by a minimum mean squared error criterion,

$$\widehat{\mathbf{x}}_k = \sum_{m=1:N_{\mathrm{S}}} \exp(\varphi_k(m))\mathbf{x}_k(m), \tag{13}$$

and the localization precision is given by

$$\widehat{\mathbf{U}}_k = \left(\sum_{m=1:N_{\mathrm{S}}} \exp\left(\varphi_k(m)\right)\left(\mathbf{x}_k(m) - \widehat{\mathbf{x}}_k\right)\left(\mathbf{x}_k(m) - \widehat{\mathbf{x}}_k\right)^{\top}\right)^{-1}. \tag{14}$$

Algorithm Design

The proposed PASS algorithm framework

Objective Function Calculation

As unveiled in Eq. (2), the intractable integral associated with inaccurate reference node location $\mathcal{N}(\mathbf{s}_j|\boldsymbol{\mu}_j, \mathbf{U}_j)$ leads to intractable objective posteriori $p(\mathbf{s}_i|\mathbf{z}_i)$. Hence, an importance sampling method is employed again. Generate the proposal particle set $\{\mathbf{s}_j(t), \wp_j(t)\,|\forall t = 1 : N_{\mathrm{M}}\}$ from $\mathcal{N}(\mathbf{s}_j|\boldsymbol{\mu}_j, \mathbf{U}_j)$, and then the objective function $f(\mathbf{x}_k(m; n))$ in Eq. (7) can be approximated as

$$f(\mathbf{x}_k(m; n)) = \ln \mathcal{P}_{\mathrm{P}}(\mathbf{x}_k(m; n)) + \sum_{j\in\Psi_i} \ln\left(\sum_{t=1:N_{\mathrm{M}}} \wp_j(t)\mathcal{P}_{\mathrm{M}}(\mathbf{x}_k(m; n), \mathbf{s}_j(t))\right), \tag{15}$$

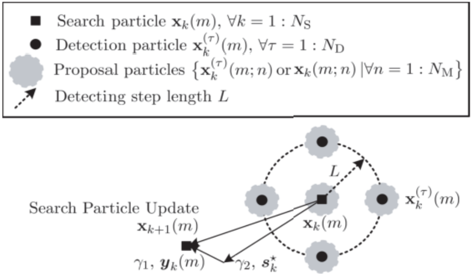
$$\mathcal{P}_{\mathrm{P}}(\mathbf{x}_k(m; n)) = \frac{(\det(\mathbf{U}_i))^{\frac{1}{2}}}{\sqrt{2\pi}} \exp\left(-\frac{1}{2}(\mathbf{x}_k(m; n) - \boldsymbol{\mu}_i)^{\top}\mathbf{U}_i(\mathbf{x}_k(m; n) - \boldsymbol{\mu}_i)\right), \tag{16}$$

$$\mathcal{P}_{\mathrm{M}}(\mathbf{x}_k(m; n), \mathbf{s}_j(t)) = \frac{|\mathrm{w}_{i,j}|^{\frac{1}{2}}}{\sqrt{2\pi}} \exp\left(-\frac{1}{2}\mathrm{w}_{i,j}(\mathrm{z}_{i,j} - h(\mathbf{x}_k(m; n), \mathbf{s}_j(t)))^2\right). \tag{17}$$

An so is $f(\mathbf{x}_k^{(\tau)}(m; n))$ in Eq. (11), wherein $\mathbf{x}_k(m; n)$ is replaced by $\mathbf{x}_k^{(\tau)}(m; n)$.

Algorithm Design

The proposed PASS algorithm framework



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Simulation Results

Simulation Settings

In addition to the PASS algorithm, the traditional PSO [1], orthogonal learning PSO [2], chaos-based accelerated PSO (APSO) [3] and importance sampling-based positioning (ISP) algorithm [4] are also simulated for comparison.

Algorithm	Complexity	Parameter Settings
Proposed PASS	$\mathcal{O}(M_i N_{\mathrm{S}} N_{\mathrm{D}} N_{\mathrm{M}}^2 \mathcal{T})$	$L = 5[\mathrm{m}], \gamma_1 = \gamma_2 = 0.25,$ $N_{\mathrm{S}} = N_{\mathrm{D}} = N_{\mathrm{M}} = 10$
Trad. PSO [1]	$\mathcal{O}(M_i N_{\mathrm{S}} \mathcal{T})$	$N_{\mathrm{S}} = 10^4$
Orth. PSO [2]	$\mathcal{O}\left(M_i N_{\mathrm{S}} M_{\mathrm{T}} \mathcal{T}\right)$	$M_{\mathrm{T}} = 4,\ N_{\mathrm{S}} = 2.5 * 10^3$
APSO [3]	$\mathcal{O}(M_i N_{\mathrm{S}} \mathcal{T})$	$N_{\mathrm{S}} = 10^4$
ISP [4]	$\mathcal{O}\left(M_i \left(N_{\mathrm{S}}\right)^2\right)$	$N_{\mathrm{S}} = 317$

Note that, in orthogonal learning PSO [2], the integer $M_{\mathrm{T}} \in [1, 2^{\mathfrak{D}}]$ stands for its test set size. Moreover, we set $\mathcal{T} = 10$, $M_i = 6, \forall i$.

[1] James Kennedy, "Particle swarm optimization." *Encyclopedia of Machine Learning*. Springer US, 2010. 760-766.
[2] Z. H. Zhan, J. Zhang, Y. Li and Y. H. Shi, "Orthogonal learning particle swarm optimization." *Evolutionary Computation, IEEE Transactions on* 15.6 (2011): 832-847.
[3] A. H. Gandomi, G. J. Yun, X. S. Yang and S. Talatahari, "Chaos-enhanced accelerated particle swarm optimization." *Communications in Nonlinear Science and Numerical Simulation* 18.2 (2013): 327-340.
[4] M. Vemula, M. F. Bugallo, P. M. Djuric, "Sensor Self-localization with Beacon Position Uncertainty," *Signal Processing*, vol.89, no.6, 2009, pp.1144-1154.

Simulation Results

Impacts of different factors

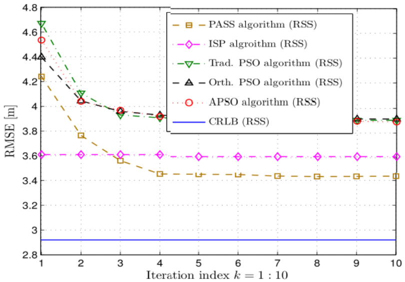

Figure: RSS-based localization errors with different methods

- The proposed PASS algorithm benefits from the harness of reference node location errors, its local detection and importance sampling.
- The traditional PSO method [1], orthogonal learning PSO [2] and APSO method [3] neglect the harness of node location errors (i.e., no proposal particles).
- The particle set used in ISP [4] is directly drawn from the priori of network node locations, so its particle representation efficiency is limited.

Thanks for your attention.
Any Question?

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