Improving Target Tracking By Incorporating Shadow Fading

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Outline

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Introduction

- Wireless localization has a broad variety of applications (indoor navigation, LBSs, health-care and etc)
- A typical localization system consists of
  - Anchors: positions are known
  - Tag: user to be located
- The tag can be located via TOA/TDOA, AOA or RSS measurements

Introduction

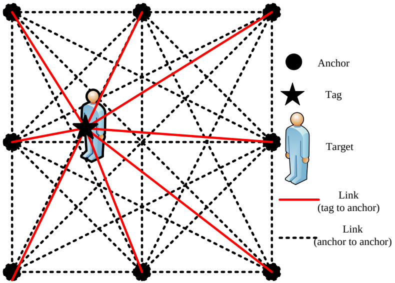
- Conventional localization methods merely consider the range measurements from tag to anchors
- The user is typically a person which can shadow the links comprised by anchors
- Exploiting shadow fading can further improve the performance of TOA-based localization methods

Outline

Proposed Method: Overview

Contributions

- Shadow fading caused by the target is exploited
- Range and shadow fading measurements are fused by particle filtering
- The Cramer-Rao bound of the hybrid approach is derived



Proposed localization scheme

Proposed Method: Notations

- $\mathbf{x}_i = (x_i, y_i)^T$:the coordinate of the anchor
- $\mathbf{x}_t = (x_t, y_t)^T$: the position of the target (tag)
- $\mathbf{X}_t = [x_t, \dot{x}_t, y_t, \dot{y}_t]$: the target state
- $d_{i,t}$: range measurement
- $r_{l,t}$: RSS measurement when the target is present
- $\bar{r}_l$: RSS measurement when the target is absent

Proposed Method: System Model

- Range measurement model

$$d_{i,t} = g_i(\mathbf{x}_t) + v_{i,t}, \tag{1}$$

where $g_i(\mathbf{x}_t) = \|\mathbf{x}_t - \mathbf{x}_i\|$

- Shadow fading measurement model

$$\Delta r_{l,t} = \bar{r}_l - r_{l,t} = h_l(\mathbf{x}_t) + u_{l,t}, \tag{2}$$

$$h_l(\mathbf{x}_t) = \phi \exp\left(-\frac{\Delta d_{l,t}}{\sigma}\right), \tag{3}$$

where $\Delta d_{l,t} = \|\mathbf{x}_t - \mathbf{x}_i\| + \|\mathbf{x}_t - \mathbf{x}_j\| - \|\mathbf{x}_i - \mathbf{x}_j\|$

Proposed Method: System Model

- Integrated measurement model

$$\mathbf{z}_t = \mathbf{f}\left(\mathbf{x}_t\right) + \mathbf{n}_t, \tag{4}$$

- Motion model

$$\mathbf{X}_t = \mathbf{F}\mathbf{X}_{t-1} + \varepsilon_t, \tag{5}$$

Proposed Method: Particle Filtering Fusion

- Particle filtering (PF) is well-known for nonlinear filtering

$$p\left(\mathbf{X}_t \left|\mathbf{z}_{1:t}\right.\right) \approx \sum_{m=1}^{M} w_t^m \delta\left(\mathbf{X}_t - \mathbf{X}_t^m\right), \tag{6}$$

- PF consists two steps: particle propagation and weight updating
- Particle propagation

$$p\left(\mathbf{X}_t^m \left|\mathbf{X}_{t-1}^m\right.\right) \sim \mathcal{N}\left(\mathbf{F}\mathbf{X}_{t-1}^m, \mathbf{Q}\right), \tag{7}$$

Proposed Method: Particle Filtering Fusion

- Weight updating

$$w_t^m \propto w_{t-1}^m p\left(\mathbf{z}_t \middle| \mathbf{X}_t^m\right), \tag{8}$$

where

$$\log p\left(\mathbf{z}_t \middle| \mathbf{X}_t^m\right) \propto \sum_{i=1}^{N} -\frac{\left(d_{i,t} - g_i\left(\mathbf{x}_t^m\right)\right)^2}{2\sigma_g^2} + \sum_{l=1}^{L} -\frac{\left(\Delta r_{l,t} - h_l\left(\mathbf{x}_t^m\right)\right)^2}{2\sigma_h^2}. \tag{9}$$

- State estimation

$$\mathbf{X}_t = \sum_{m=1}^{M} w_t^m \mathbf{X}_t^m. \tag{10}$$

Proposed Method: PCRLB

- The variance of estimation error is bounded by

$$\mathrm{E}\left[\left(\mathbf{X}_t - \mathbf{X}_t\right)\left(\mathbf{X}_t - \mathbf{X}_t\right)^T\right] > \mathbf{J}_t^{-1}, \tag{11}$$

where

$$\mathbf{J}_t = \left(\mathbf{Q} + \mathbf{F}\mathbf{J}_{t-1}^{-1}\mathbf{F}^T\right)^{-1} + \mathbf{H}^T\mathbf{J}\left(\mathbf{x}_t\right)\mathbf{H}, \tag{12}$$

- $\mathbf{H} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix}^T$, $\mathbf{J}\left(\mathbf{x}_t\right) = \begin{bmatrix} \mathbf{J}_{11} & \mathbf{J}_{12} \\ \mathbf{J}_{21} & \mathbf{J}_{22} \end{bmatrix}$

Proposed Method: PCRLB

$$\begin{aligned}
\mathbf{J}_{11} &= \frac{1}{\sigma_g^2}\sum_{i=1}^{N}\left(\frac{\partial g_i(\mathbf{x}_t)}{\partial x_t}\right)^2 + \frac{1}{\sigma_h^2}\sum_{l=1}^{L}\left(\frac{\partial h_l(\mathbf{x}_t)}{\partial x_t}\right)^2, \\
\mathbf{J}_{22} &= \frac{1}{\sigma_g^2}\sum_{i=1}^{N}\left(\frac{\partial g_i(\mathbf{x}_t)}{\partial y_t}\right)^2 + \frac{1}{\sigma_h^2}\sum_{l=1}^{L}\left(\frac{\partial h_l(\mathbf{x}_t)}{\partial y_t}\right)^2, \\
\mathbf{J}_{12} &= \mathbf{J}_{21} = \frac{1}{\sigma_g^2}\sum_{i=1}^{N}\frac{\partial g_i(\mathbf{x}_t)}{\partial x_t}\frac{\partial g_i(\mathbf{x}_t)}{\partial y_t} \\
&\quad + \frac{1}{\sigma_h^2}\sum_{l=1}^{L}\frac{\partial h_l(\mathbf{x}_t)}{\partial x_t}\frac{\partial h_l(\mathbf{x}_t)}{\partial y_t},
\end{aligned} \tag{13}$$

Outline

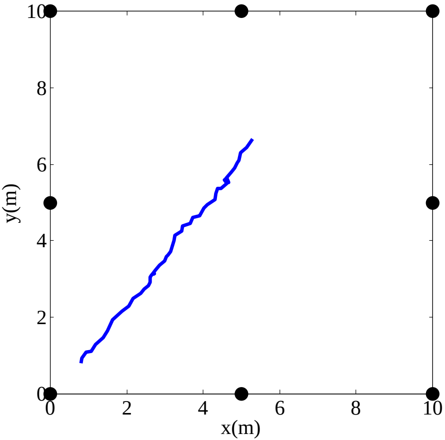
Simulation Results

- Number of anchors: 8
- Monitored region : 10m $\times$ 10m
- Number of instants: 50
- $\mathbf{x}_0 = [0.8, 1.5, 0.8, 1.5]^T$
- $\mathbf{J}_0 =$ diag $(0.5, 0.5, 0.5, 0.5)$
- Other parameters: see Table.I

Values of the parameters

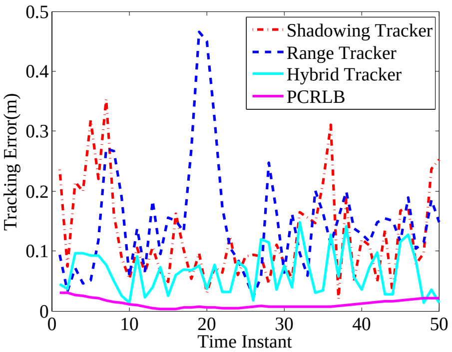
ϕ [dB]	8	σ_h [dB]	1
δ	0.05	q	0.1
σ_g [m]	0.1	Δt[s]	0.05

Simulation Results



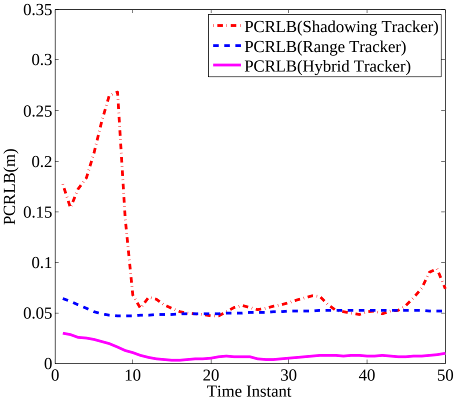
- Simulated trajectory of the target

Simulation Results



- Tracking error is averaged by 100 Monte Carlo runs

Simulation Results



- The hybrid tracker has the lowers PCRLB

Outline

Conclusion

- A hybrid target tracking approach which employs both shadowing fading and range of links is presented.
- We fusion the two kinds of measurements under Bayesian filter framework to optimally track the target
- Effectiveness of the method is verified by simulations

Thank you!