LISC

LABORATORY FOR INTELLIGENT SYSTEMS AND CONTROLS

Optimized Visibility Motion Planning for Target Tracking and Localization

Hongchuan Wei[1], Wenjie Lu[1], **Pingping Zhu**[1], Guoquan Huang[2], John Leonard[3], Silvia Ferrari[1]

[1] Duke University

[2] University of Delaware

[3] Massachusetts Institute of Technology

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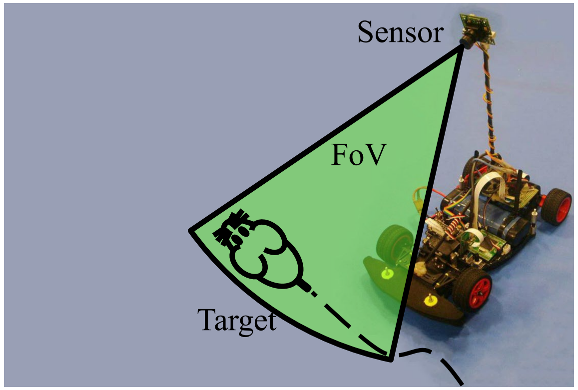
Introduction and Motivation

- **Applications of tracking moving targets using mobile robotic sensors**

  -- Environmental and atmospheric monitoring and surveillance

  -- Security and surveillance

  -- Tracking of endangered species



- **Abilities of tracking and localization limited by**

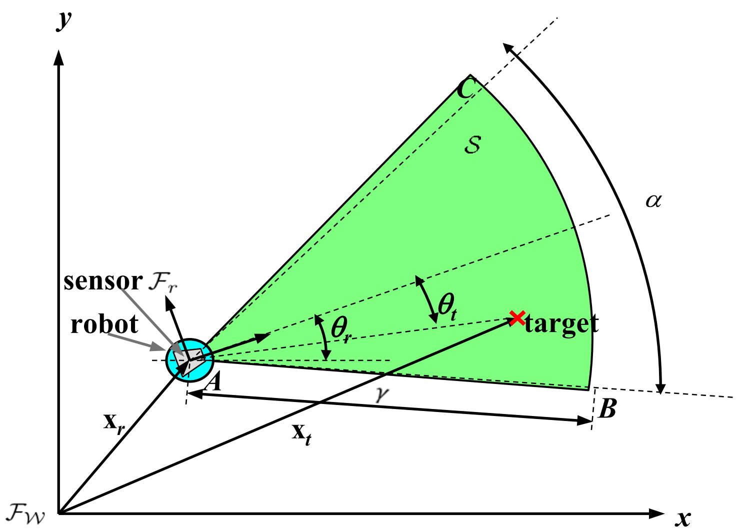
  -- Absence of global positioning system (GPS)

  -- Bounded field-of-view (FoV) or visibility region

  -- Target loss -> unbounded tracking error

- **Motivation:** **Reduce target loss rate**

Problem Formulation



State Models:

Mobile robotic sensor dynamics: unicycle model

$$\mathbf{q}_r(k+1) \triangleq \mathbf{f}_r[\mathbf{q}_r(k), \mathbf{u}_k(k)] = \mathbf{q}_r(k) + \mathbf{B}_r(k)\mathbf{u}_r(k)$$

$$\mathbf{B}_r(k) = \begin{bmatrix} \cos\theta_r(k)\delta t & 0 \\ \sin\theta_r(k)\delta t & 0 \\ 0 & \delta t \end{bmatrix},$$

$$\mathbf{q}_r(k) = \begin{bmatrix} x_r & y_r & \theta_r \end{bmatrix}^T \text{and } \mathbf{u}_r(k) = \begin{bmatrix} v_r & \omega_r \end{bmatrix}$$

Target dynamics: linear stochastic motion model

$$\mathbf{q}_t(k+1) \triangleq \mathbf{f}_t[\mathbf{q}_t(k)] + \mathbf{w} = \Phi_t \mathbf{q}_t(k) + \mathbf{w}$$

$$\mathbf{q}_t = \begin{bmatrix} x_t & y_t & \dot{x}_t & \dot{y}_t \end{bmatrix}^T \text{ and } \mathbf{w} \sim \mathcal{N}(\mathbf{0}, \mathbf{Q}_r)$$

Measurement Models:

target measurements:

$$\mathbf{z}_t(k) \triangleq \mathbf{h}_t(\mathbf{q}_r, \mathbf{q}_t) = \begin{cases} \begin{bmatrix} \rho_t & \theta_t \end{bmatrix}^T + \mathbf{v}_t, & \mathbf{x}_t \in \mathcal{S}(\mathbf{q}_r) \\ \emptyset, & \mathbf{x}_t \notin \mathcal{S}(\mathbf{q}_r) \end{cases}$$

proprioceptive sensor measurements:

$$\mathbf{z}_r(k) \triangleq \mathbf{h}_r[\mathbf{u}_k(k)] = \mathbf{u}_k(k) + \mathbf{v}_k(k)$$

landmark measurements:

$$\mathbf{z}_{l_i} \triangleq \mathbf{h}_l(\mathbf{q}_r, \mathbf{x}_{l_i}) = \begin{cases} \begin{bmatrix} \rho_{l_i} & \theta_{l_i} \end{bmatrix}^T + \mathbf{v}_l, & \mathbf{x}_{l_i} \in \mathcal{S}(\mathbf{q}_r) \\ \emptyset, & \mathbf{x}_{l_i} \notin \mathcal{S}(\mathbf{q}_r) \end{cases}$$

$$\rho_t = \|\mathbf{x}_r - \mathbf{x}_t\|^2$$

$$\rho_{l_i} = \|\mathbf{x}_r - \mathbf{x}_{l_i}\|^2$$

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EKF-based Robot Localization and Target Tracking

Joint State Models: $\mathbf{q}(k+1) = \mathbf{f}\left[\mathbf{q}(k), \mathbf{u}(k)\right] = \begin{bmatrix} \mathbf{f}_r\left[\mathbf{q}_r(k), \mathbf{u}_r(k)\right] \\ \mathbf{f}_t\left[\mathbf{q}_t(k)\right] \end{bmatrix}$ $\quad \mathbf{q}(k) = \begin{bmatrix} \mathbf{q}_r(k) \\ \mathbf{q}_t(k) \end{bmatrix}$

Jacobian Matrix: $\boldsymbol{\Phi}(k) = \begin{bmatrix} \boldsymbol{\Phi}_r(k) & \mathbf{0} \\ \mathbf{0} & \boldsymbol{\Phi}_t \end{bmatrix}$

$$\boldsymbol{\Phi}_r(k) \triangleq \frac{\partial}{\partial \mathbf{q}_r(k)} \mathbf{f}_r\left[\mathbf{q}_r(k), \mathbf{u}_r(k)\right]$$

Joint Measurement Models: $\mathbf{z}(k) = \mathbf{h}\left[\mathbf{q}(k)\right]$ $\quad \mathbf{h} = \begin{bmatrix} \mathbf{h}_t^T & \mathbf{h}_{l_1}^T & \dots & \mathbf{h}_{l_L}^T \end{bmatrix}^T$

Jacobian Matrix: $\mathbf{H}(k) \triangleq \frac{\partial}{\partial \mathbf{q}(k)} \mathbf{h}\left[\mathbf{q}(k)\right]$

EKF is applied to estimated the joint states from joint measurements

Visibility-based Robot Motion Planning

Tracking and Localization Performance can be represented by

the expected power of the error between the true and estimated robot-target joint states

$$J\left[\mathbf{u}_r(k)\right] = (1-P_d)\mathbb{E}\left[\mathbf{e}(k+1|k)^T\mathbf{e}(k+1|k)\right] + P_d\mathbb{E}\left[\mathbf{e}(k+1|k)^T\mathbf{e}(k+1|k)\right]$$

where

$$\mathbf{e}(k+1|k) = \mathbf{q}(k) - \hat{\mathbf{q}}(k+1|k) \text{ and } \mathbf{e}(k+1|k+1) = \mathbf{q}(k) - \hat{\mathbf{q}}(k+1|k+1)$$

Target-detection probability : $P_d\left[\mathbf{q}_r(k)\right] = \int_{\mathcal{S}[\mathbf{q}_r(k)]} f_t\left[\mathbf{x}_t(k)\right] d\mathbf{x}_t(k)$

Simplified expected power of the error

$$J\left[\mathbf{u}_r(k)\right] = \text{tr}\left[\mathbf{P}_t(k|k+1)\right] - P_d \times \left\{\text{tr}\left[\mathbf{P}_t(k|k-1)\right] - \text{tr}\left[\mathbf{P}_t(k+1|k+1)\right]\right\}$$

Assumption: $\text{tr}\left[\mathbf{P}_t(k|k-1)\right] - \text{tr}\left[\mathbf{P}_t(k+1|k+1)\right] \geq 0$

Robot Control Law:

$$\mathbf{u}_r(k) = \max_{\mathbf{u}_r(k)} P_d\left[\mathbf{q}_r(k+1)\right]$$
$$\text{s.t. } \mathbf{q}_r(k+1) = \mathbf{q}_r(k) + \mathbf{B}_r(k)\mathbf{u}_k(k)\delta t$$

Visibility-based Robot Motion Planning

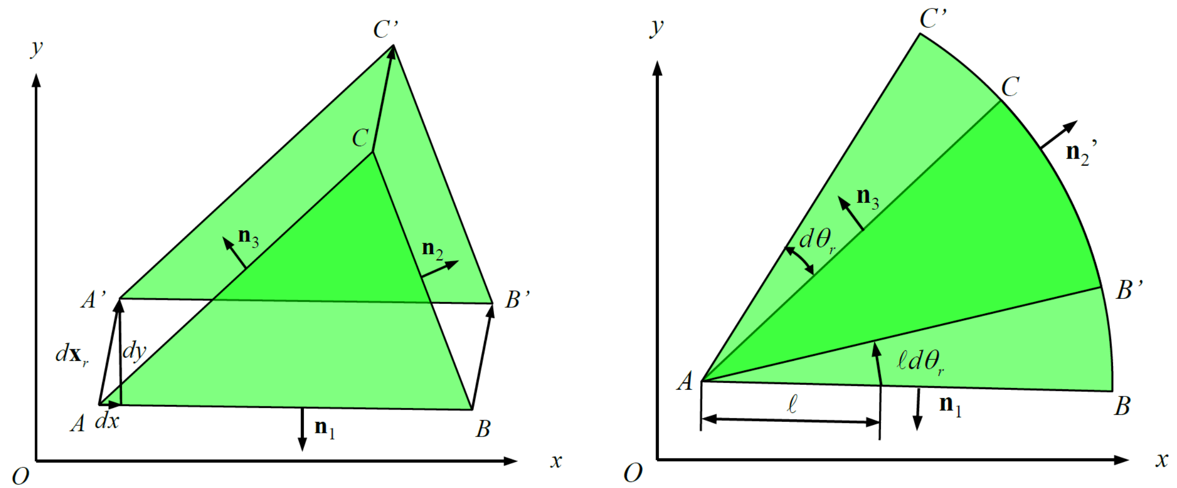
Robot Control Law is obtained by moving in the direction of the adjoined gradient

$$\frac{\partial P_d[\mathbf{q}_r(k+1)]}{\partial \mathbf{u}_r(k)} = \frac{\partial P_d[\mathbf{q}_r(k+1)]}{\partial \mathbf{q}_r(k+1)} \frac{\partial \mathbf{q}_r(k+1)}{\partial \mathbf{u}_r(k)}$$

The first term: the change of the robot FoV due to translation and rotation of the robot

Translation: $\frac{\partial}{\partial x_r} P_d \left[\mathbf{q}_r(k+1)\right]$ and $\frac{\partial}{\partial y_r} P_d \left[\mathbf{q}_r(k+1)\right]$

Rotation: $\frac{\partial}{\partial \theta_r} P_d \left[\mathbf{q}_r(k+1)\right]$



(a) translation (b) rotation

The second term: $\frac{\partial \mathbf{q}_r(k+1)}{\partial \mathbf{u}_r(k)} = \mathbf{B}_r(k)\delta t$

Optimized-Visibility Algorithm

Procedure FindOptimalControl$(f_t(\mathbf{x}_t), \mathcal{U}, \epsilon)$

$\mathbf{u}_r = \mathbf{u}_0$
while(1)
  $\mathbf{u}'_r \leftarrow \mathbf{u}_r + \eta \frac{\partial}{\partial \mathbf{u}_r(k)} \{P_d[\mathbf{q}_r(k+1)]\}$
  if $\mathbf{u}'_r \notin \mathcal{U}$
    break
  elseif $\|\mathbf{u}'_r - \mathbf{u}_r\| \leq \epsilon$
    break
  else
    $\mathbf{u}_r \leftarrow \mathbf{u}'_r$
  endif
endwhile
return $\mathbf{u}_r$

Simulation Results

❖ Comparison

The proposed algorithm is compared with a state-of-the-art potential field approach

Potential force: $\mathrm{f}_p(k) = c_p \|\mathrm{x}_p(k) - \mu_t(k)\|$

$\mathrm{x}_p(k)$: the center of the inscribed circle of the FoV
$\mu_t(k)$: the estimated mean of target position distribution

Control:

$$v_r(k) = a_p \|\mathrm{f}_p(k)\| \cos\theta_p(k)$$
$$\omega_r(k) = b_p \|\mathrm{f}_p(k)\| \sin\theta_p(k)$$

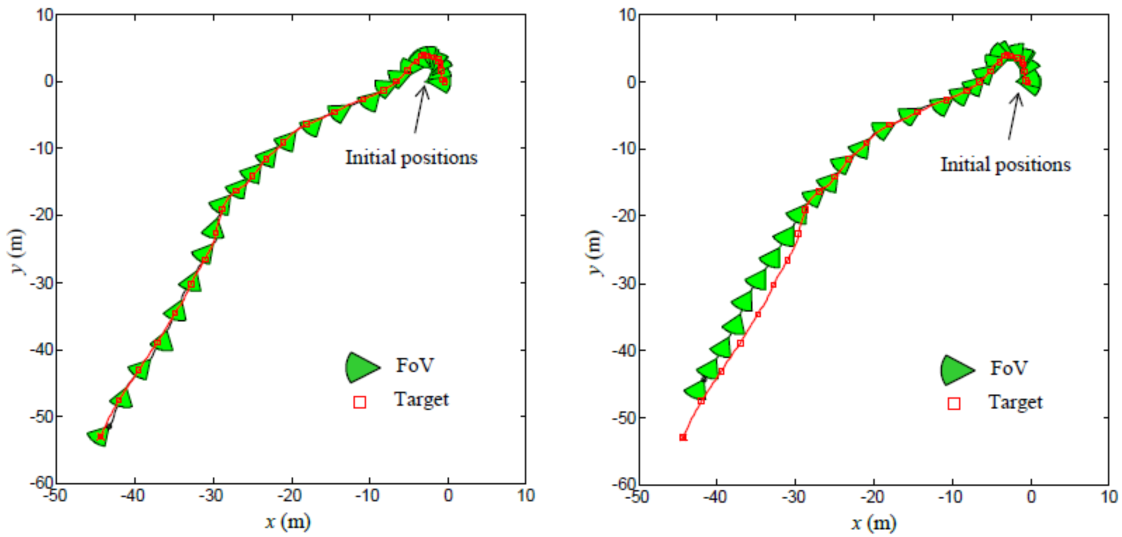
❖ Experimental setting

- Workspace: $\mathcal{W} = [-50, 50] \times [-50, 50] \ \mathrm{m}^2$
- FoV: a sector with a radius $\gamma = 2.5 \ \mathrm{m}$ and an opening angle $\alpha = \pi/6 \ \mathrm{rad}$
- Target state transition matrix:

$$\Phi_t = \begin{bmatrix} 1 & 0 & \delta t & 0 \\ 0 & 1 & 0 & \delta t \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

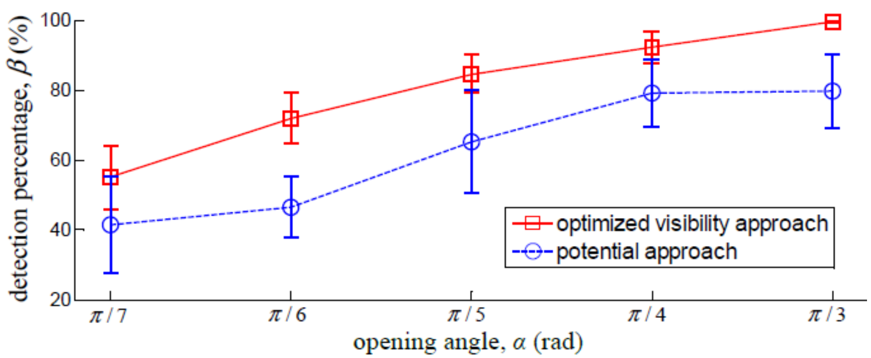
Simulation Results

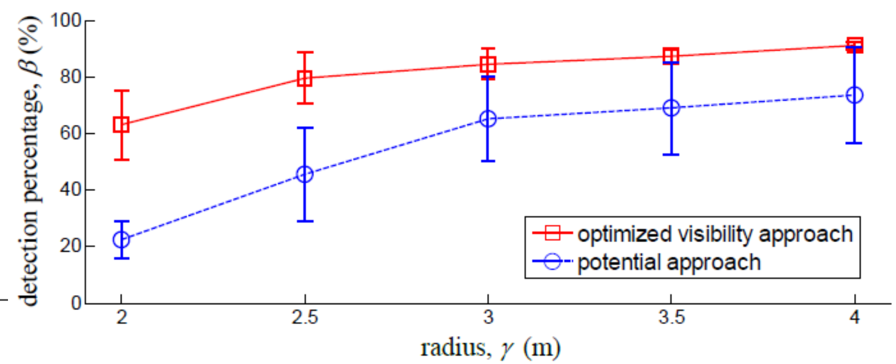
Performance with $\gamma = 2.5$ m $\alpha = \pi/6$ rad



(a) optimized-visibility approach (b) potential approach

Comparison with different FoV parameters





Conclusion and Future Work

Conclusion:

- ❖ Joint states and measurements
- ❖ EKF is applied to estimated the joint states from joint measurements
- ❖ Maximizing the target-detection probability -> Robot Control Law
- ❖ Outperform the state-of-the-art potential field approach

Future Work:

- ❖ Extend one-step-ahead optimization to multiple-step-ahead optimization
- ❖ Generalize current method to simultaneous localization, mapping and target tracking problems
- ❖ Investigate different estimation algorithm