上海自主智能无人系统科学中心
Shanghai Research Institute for Intelligent Autonomous Systems

同濟大學
TONGJI UNIVERSITY

面向群体机器人移动距离最小化的粒子群算法

Moving-distance-minimized PSO for Mobile Robot Swarm

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Layout

- Background
- Problem Statement
- Proposed Algorithm
- Experimental Results
- Conclusions

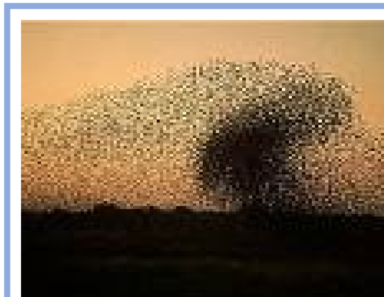
Background

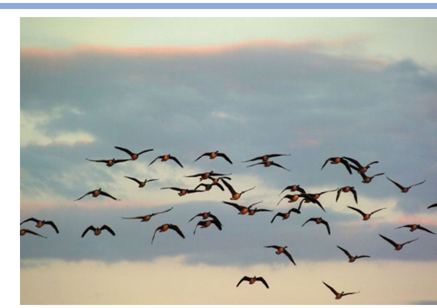
Swarm Intelligence:

Background

Swarm Intelligence:

- Evolutionary Algorithms（EA)
- Genetic Algorithm（GA)
- Ant Colony Optimization（ACO)
- **Particle Swarm Optimization（PSO)**
- Differential Evolution（DE)
- Artificial Bee Colony（ABC)
- Fireworks Algorithm（FWA)



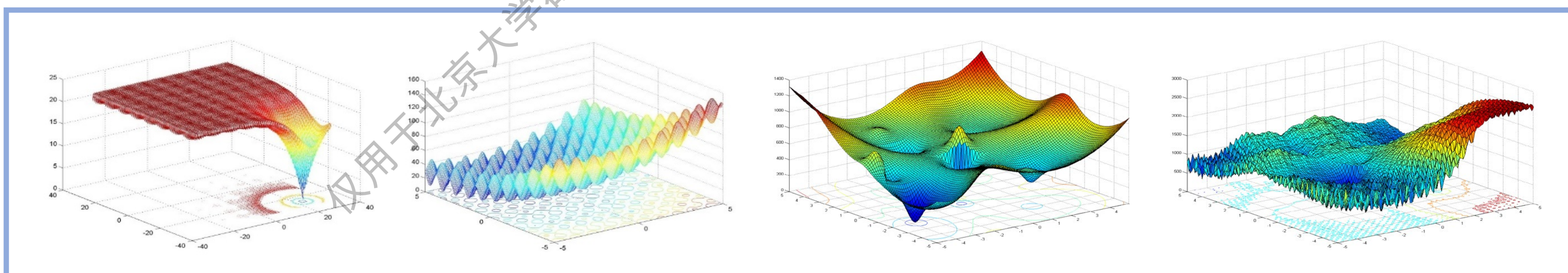
Background

Particle Swarm Optimization:

$$v_i^d = v_i^d + c_1 r_1^d\left(pbest_i^d - x_i^d\right) + c_2 r_2^d\left(gbest^d - x_i^d\right)$$

$$x_i^d = x_i^d + v_i^d$$

- Stochastic global optimization techniques
- Asymptotically, fast convergence, simple parameters



Background

Noisy-free environment :

Parameters Configurations

- PSO with inertia weight
- PSO with Time Varying Acceleration Coefficient (PSO-TVAC)
- Adaptive PSO (APSO)
- …

Topology Structure

- PSO with a ring and a von Neumann topology
- Fully informed particle swarm (FIPS)
- Comprehensive learning PSO (CLPSO)
- …

Hybrid PSO

- Genetic learning PSO (GLPSO)
- PSO with an aging leader and challengers (ALC-PSO)
- Scatter learning PSO (SLPSO)
- …

Multiswarm Techniques

- Segment-based predominant learning swarm optimizer (SPLSO)
- PSO with an interswarm interactive learning strategy (IILPSO)
- …

Background

Noisy environment:

- PSO with Equal Resampling (PSO-ER)
- PSO with Optimal Computing Budget Allocation (PSO-OCBA)
- PSO with Learning Automata (PSO-LA)
- …

Resampling $\xrightarrow[\text{change}]{\text{noise}}$

- Noise decrease: sampling waste
- Noise increase: undersampling

Background

Our prior work：

Dual-Environmental Particle Swarm Optimizer (DEPSO)

✓ Achieve SOTA level in both noise and noise-free environment

Top-k particles → Search center → Guide the swarm

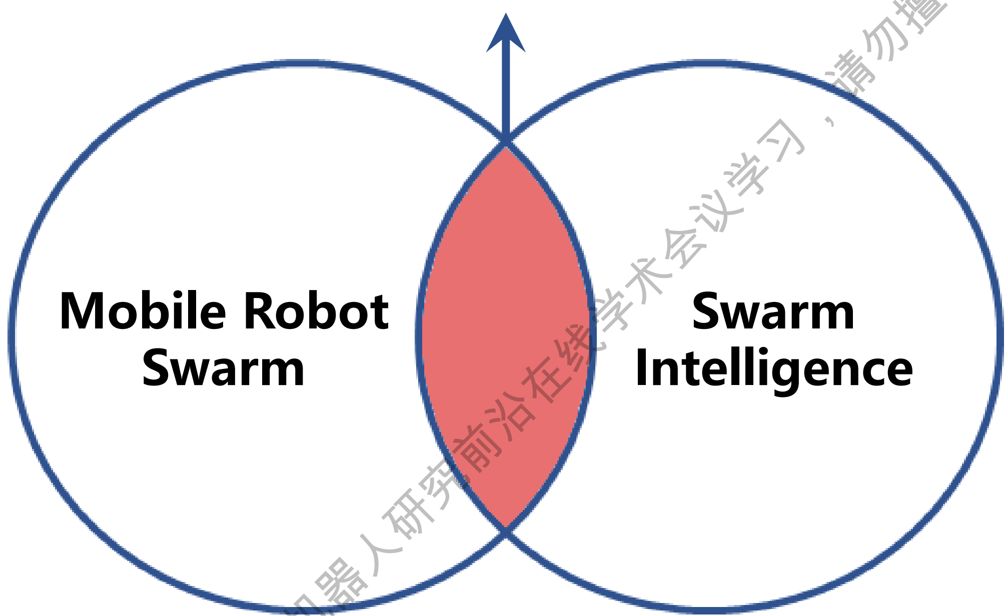
Search center: $$\theta(t) = \sum_{i=1}^{k} W_i(t) \times X_i(t)$$

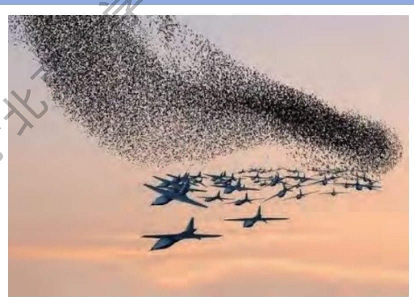
Noise variance reduction: $$\sigma_\theta^2 = \sum_{i=1}^{k} W_i^2 \sigma^2 < \sum_{i=1}^{k} W_i \sigma^2 = \sigma^2$$

- **JunQi Zhang***, XiXun Zhu, YuHeng Wang， MengChu Zhou*, "Dual-Environmental Particle Swarm Optimizer in Noisy and Noise-free Environments", ***IEEE Trans. On Cybernetics (1区，IF: 11.079)***, vol. 49, no. 6, pp. 2011-2021, 2019(SCI, EI).

Background

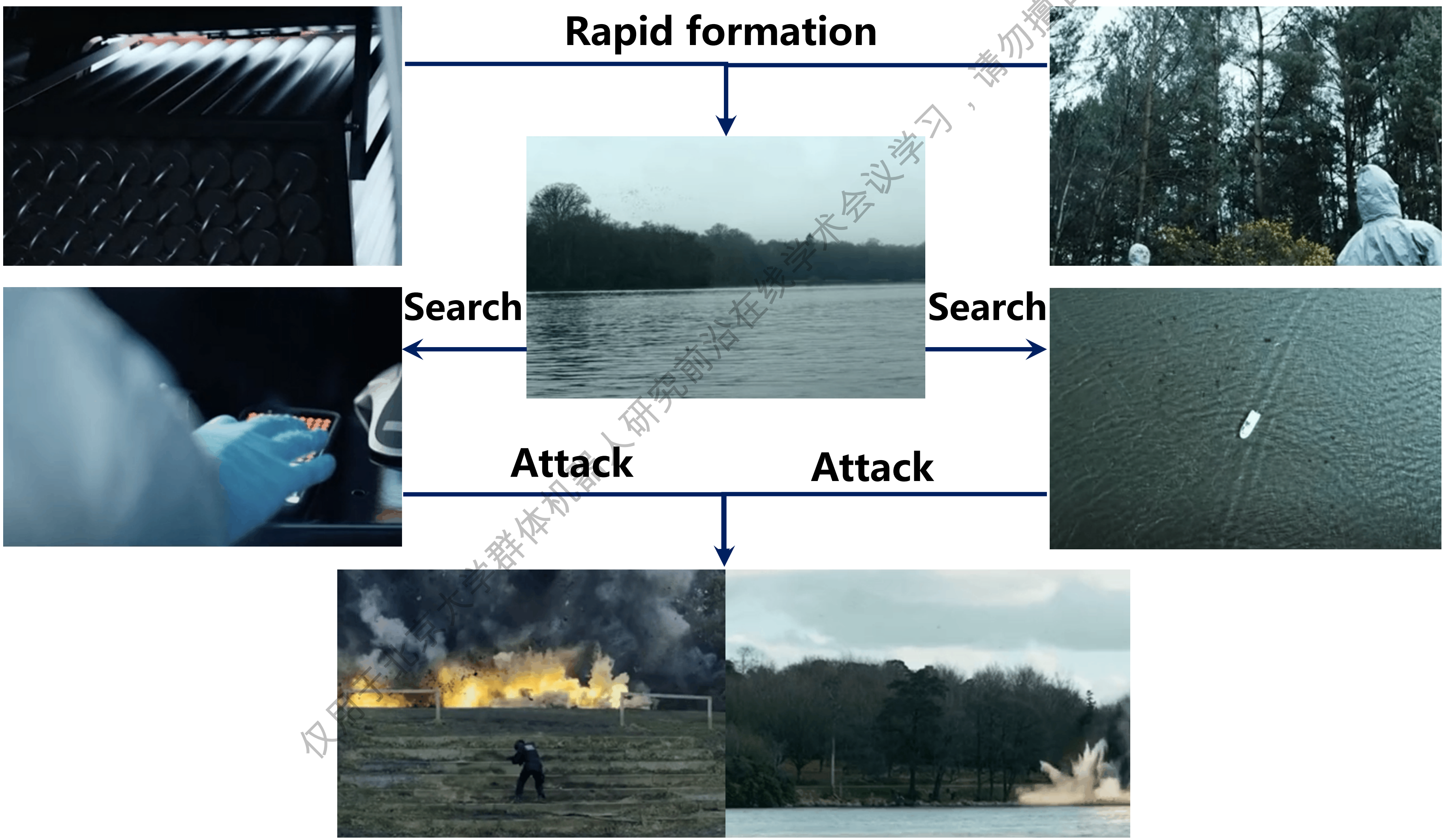
Our Research Focus



Background

Movie “Angel Has Fallen”



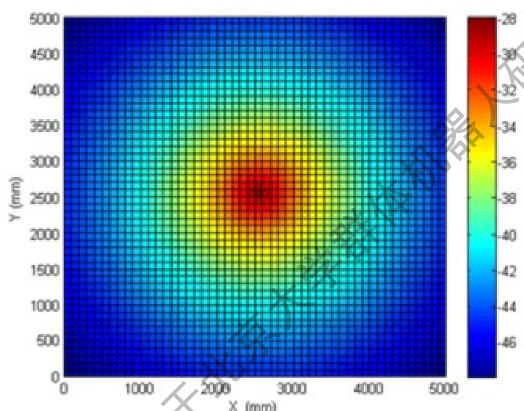
Background

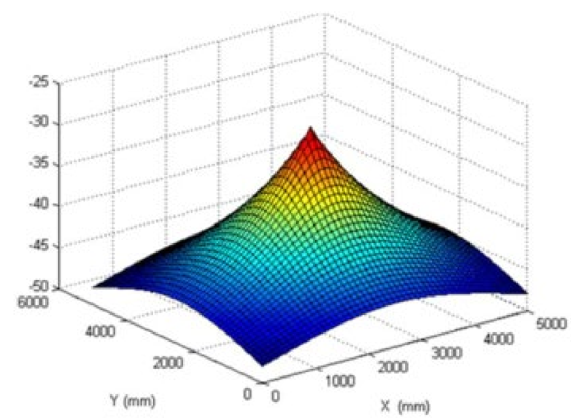
Source location problem:

measuring field
strength by sensors

Mobile robot swarm → **Locate the source**

collaborative search



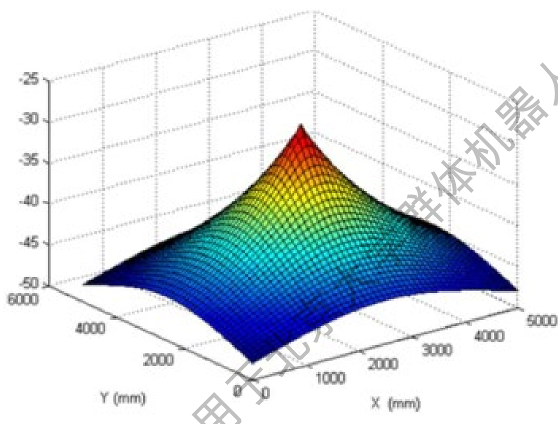


Theoretical decay profile of an electromagnetic source

Background

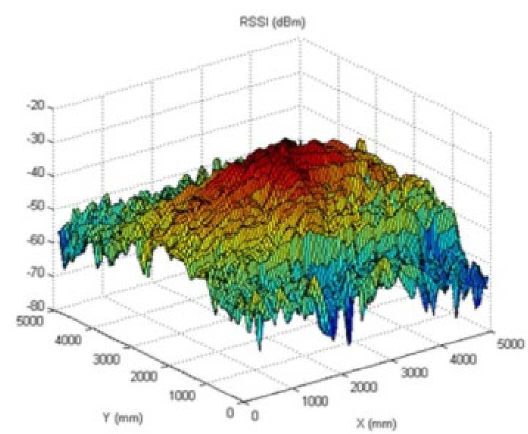
Challenges:

- No information about environment initially.
- Obstacles, reflection, refraction, and multi-path fading influence the decay profile dramatically.
- Energy and time constraints.



single-mode

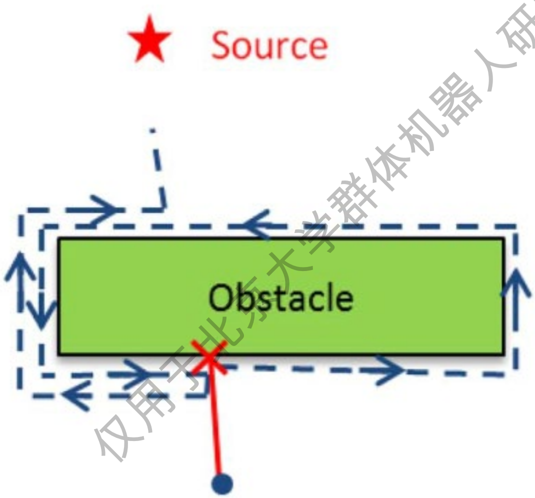
Noise

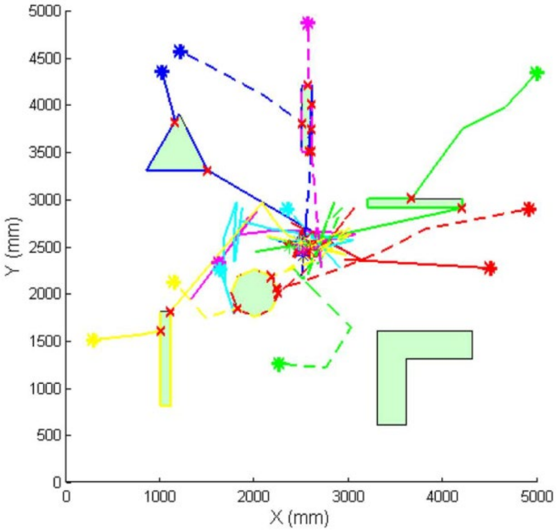


multi-mode

Background

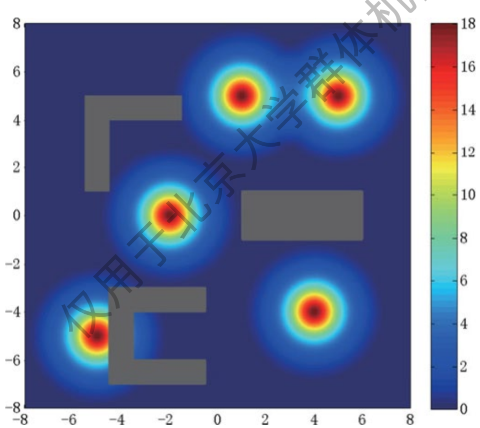
- ◻ Zou R , Kalivarapu V , Winer E , et al. Particle Swarm Optimization Based Source Seeking[J]. ***IEEE Transactions on Automation Science & Engineering***, 2015, 12(3):865-875.
  - ➢ Directly use existing PSO variants to control mobile robots to solve source location problem.
  - ➢ Consider obstacle avoidance (static / dynamic obstacles).

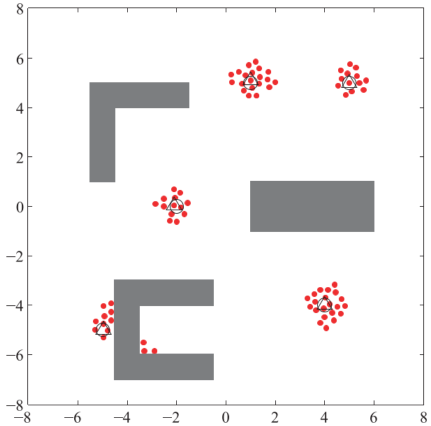




Background

- Tang Q , Ding L , Yu F , et al. Swarm Robots Search for Multiple Targets Based on an Improved Grouping Strategy[J]. ***IEEE/ACM Transactions on Computational Biology & Bioinformatics*** , 2018 , 15(6):1943-1950.
- Solve multi-source locating problem.
  - First Stage： Particles search randomly → Group by fitness value.
  - Second Stage： Each group locates the source according to PSO.
- Consider static obstacle avoidance (Rotate 15°).

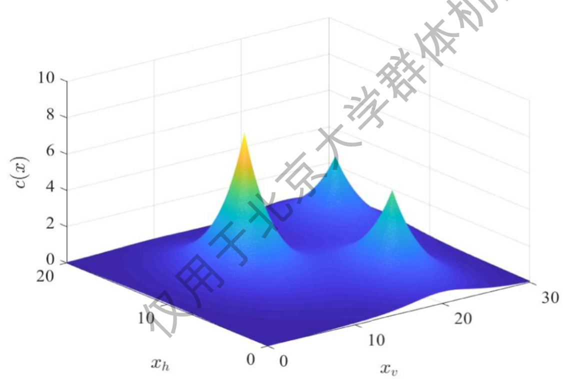


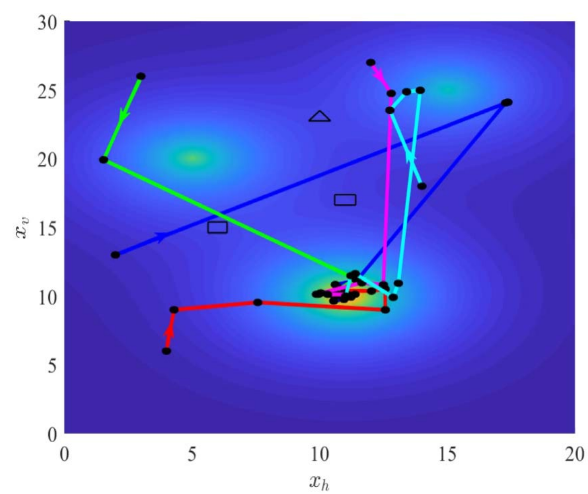


Background

- ☐ Rui-Guo Li, and Huai-Ning Wu. "Multi-Robot Source Location of Scalar Fields by a Novel Swarm Search Mechanism With Collision/Obstacle Avoidance." ***IEEE Transactions on Intelligent Transportation Systems***, 2020, DOI: 10.1109/TITS.2020.3010056.

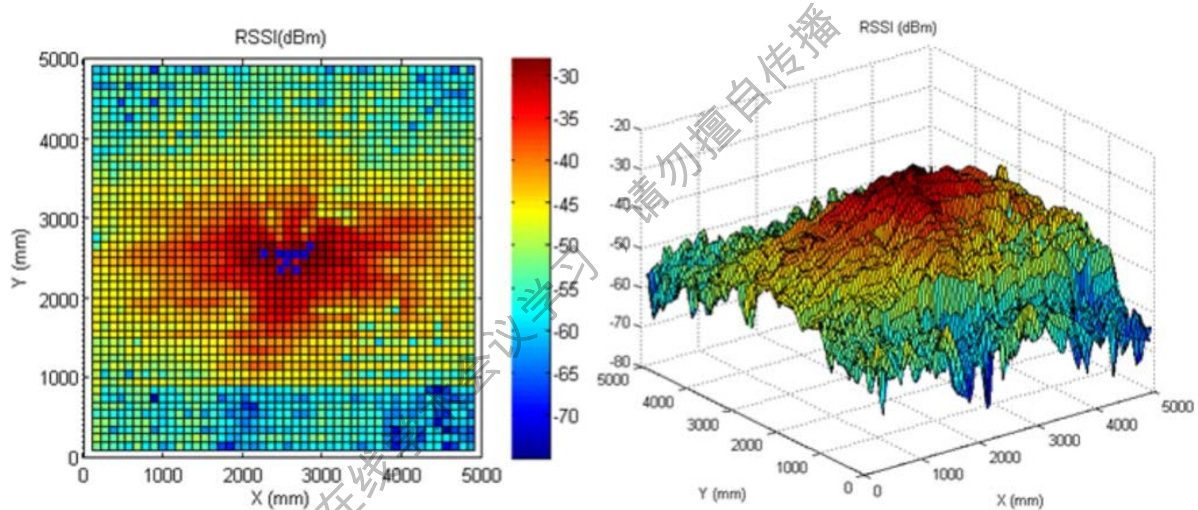
- ➢ Improve the PSO algorithm for a more efficient search.
  - Propose quantum-leading-following-based optimization (QLFBO)
- ➢ Consider obstacle avoidance (static / dynamic obstacles).
  - Artifical Potential Field



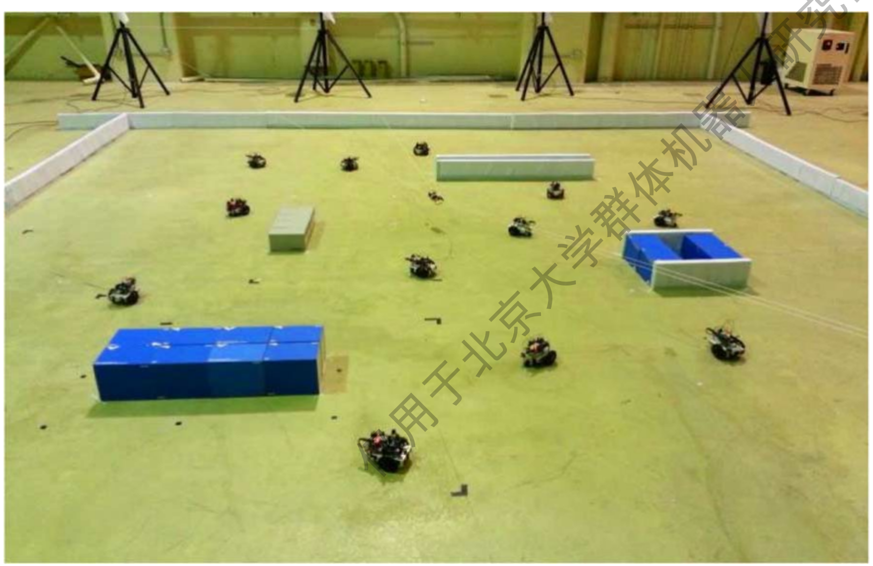


Background

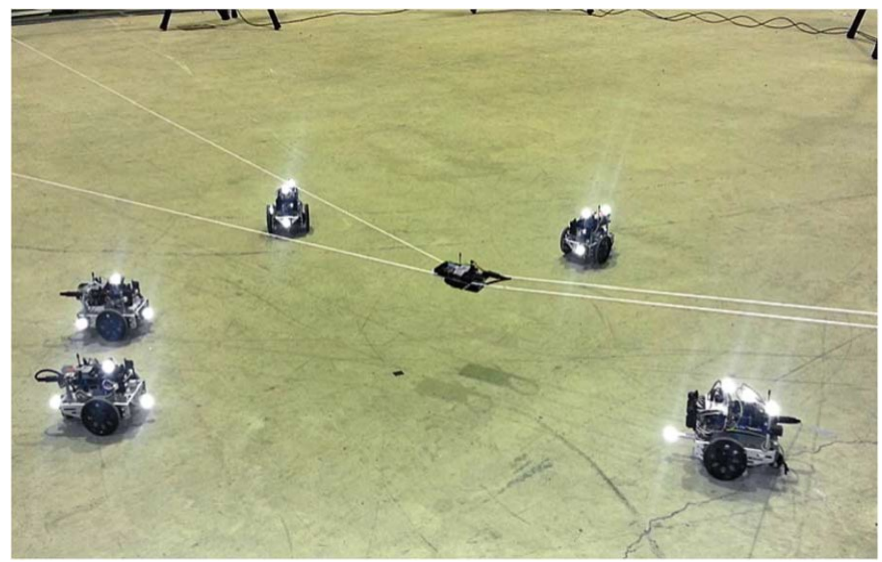
Physical Experiment:



Signal intensity distribution



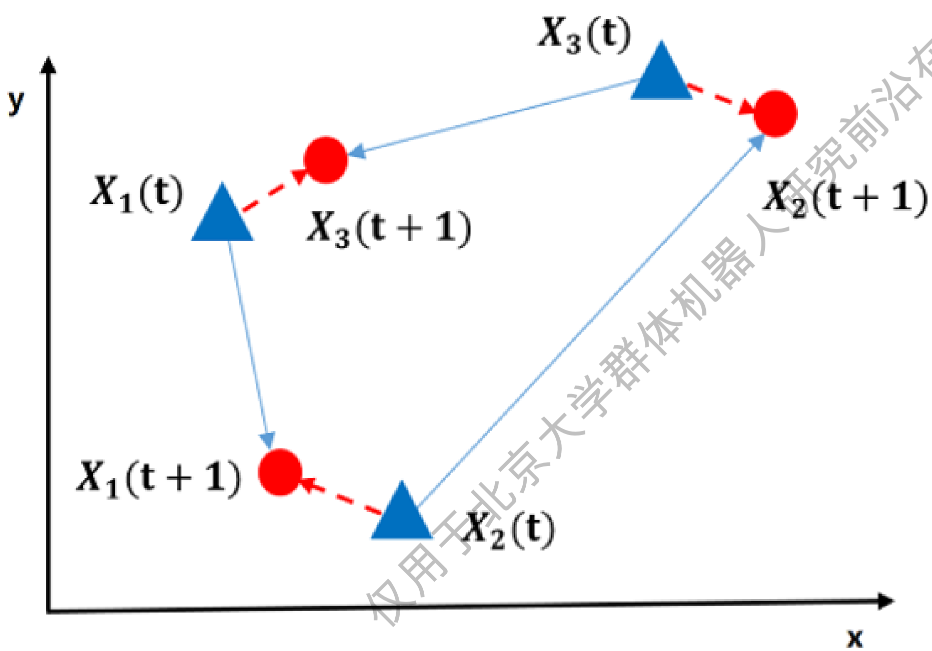
Search



Rendezvous to the source

Problem Statement

Currently, no PSO has considered the issue of particles' moving distance.



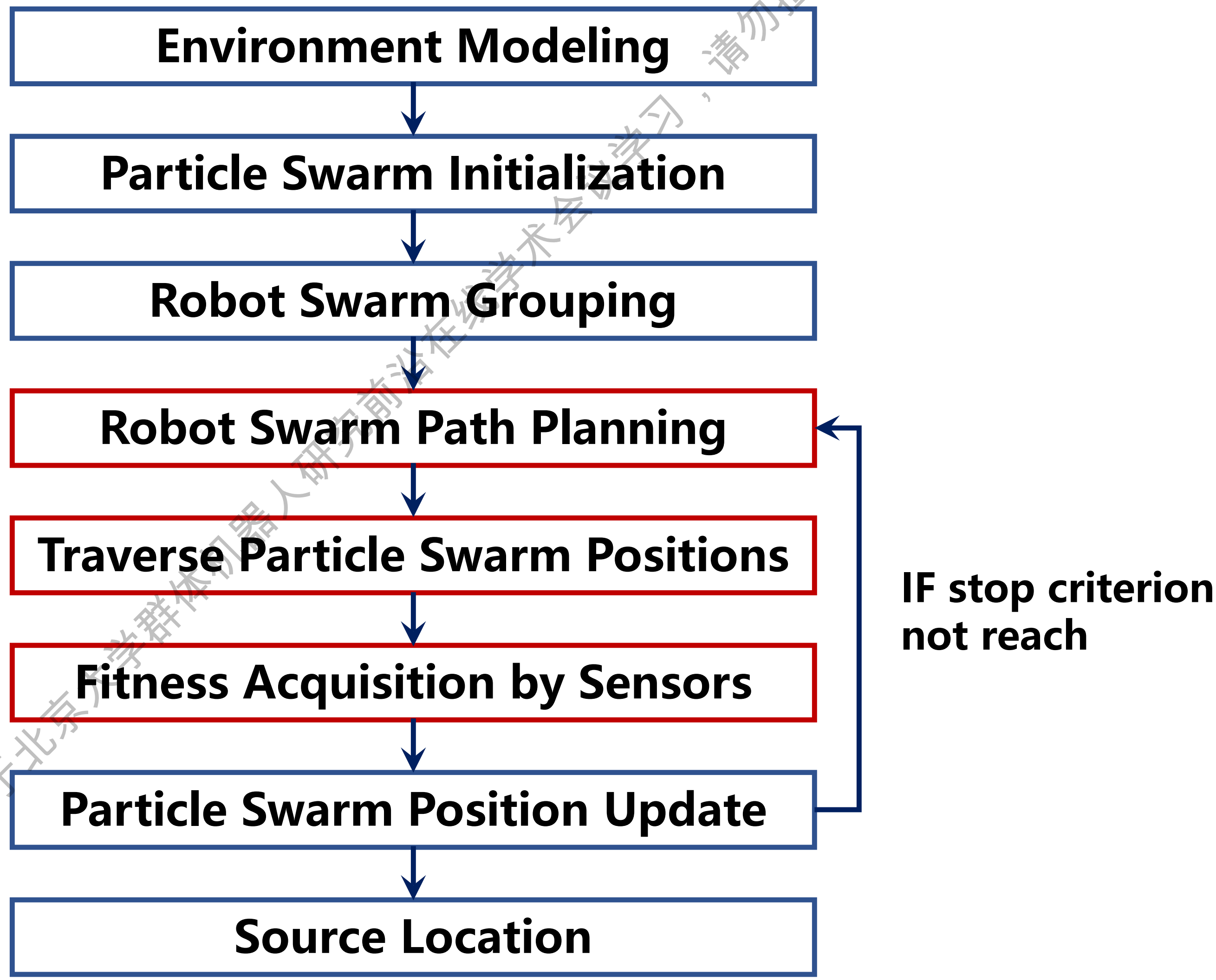
In PSO, every particle will produce a target position in each generation. In the figure:

$$X_1(t) \rightarrow X_1(t+1)$$
$$X_2(t) \rightarrow X_2(t+1)$$
$$X_3(t) \rightarrow X_3(t+1)$$

which is shown as blue solid lines. However, the red dotted lines are much better.

Proposed Algorithm

Moving-distance-minimized PSO (MPSO) Framework：



Proposed Algorithm

- The problem is converted as follows:

  In each generation, n particles produce n target positions and m robots should **visit all these positions but only once**.

- In the meanwhile, two metrics should be minimized:

  Moving Distance (→ Energy) **Makespan** (→ Efficiency)

Cost Function:

$$\Theta = a * \Omega + (1 - a) * \Delta$$

Ω and Δ indicate the total moving distance and time of the mobile robot swarm after normalization, $a \in [0,1]$ is a weight parameter.

The goal of the algorithm is to minimize this cost function Θ.

Problem Statement

Approximate Normalization:

- Ω: Moving distance
- Δ: Moving time

$\longrightarrow$ Under different orders of magnitude

- E_Ω: Estimated maximum value of Ω
- E_Δ: Estimated maximum value of Δ

$$\boxed{\Omega \xrightarrow{/E_\Omega} [0,1]} \qquad \boxed{\Delta \xrightarrow{/E_\Delta} [0,1]}$$

Proposed Algorithm

Robot Swarm Path Planning:

1: Initialize the makespan of each robot $\tau_{[1\times m]}=\{0,\dots,0\}$;

2: Initialize the cost matrix $F_{[m\times n]}$;

3: Calculate minimum value of cost matrix $F_{[i,j]}$, then let $i\ th$ robot move to $j\ th$ target position X_j, and X_j cannot be visited again later;

$$\begin{bmatrix} f_{1,1} & \cdots & f_{1,m} \\ \vdots & \ddots & \vdots \\ f_{n,1} & \cdots & f_{n,m} \end{bmatrix}_{n\times m} \rightarrow \begin{bmatrix} f_{1,1} & \cdots & f_{1,j-1} & f_{1,j+1} & \cdots & f_{1,m} \\ \vdots & \vdots & \vdots & \vdots & \cdots & \vdots \\ f_{n,1} & \cdots & f_{n,j-1} & f_{n,j+1} & \cdots & f_{n,m} \end{bmatrix}_{n\times(m-1)}$$

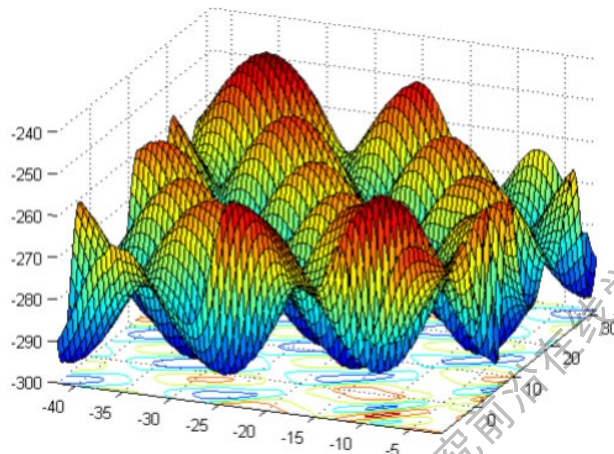
4: Update $\tau_{[1\times m]}$ and $F_{[m\times n]}$, if all target positions are visited, go to 5, otherwise, go to 3;

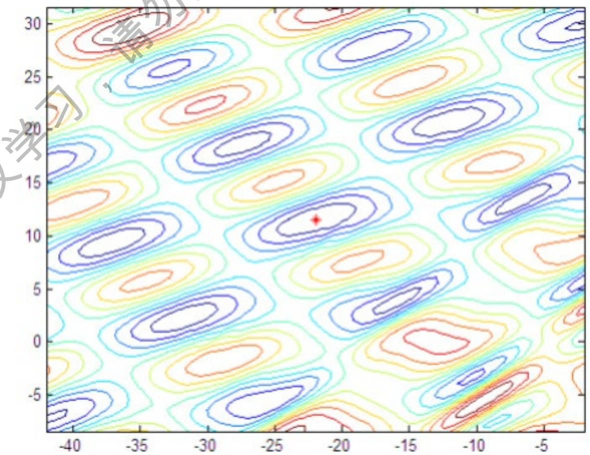
5: Path planning success.

Experimental Results

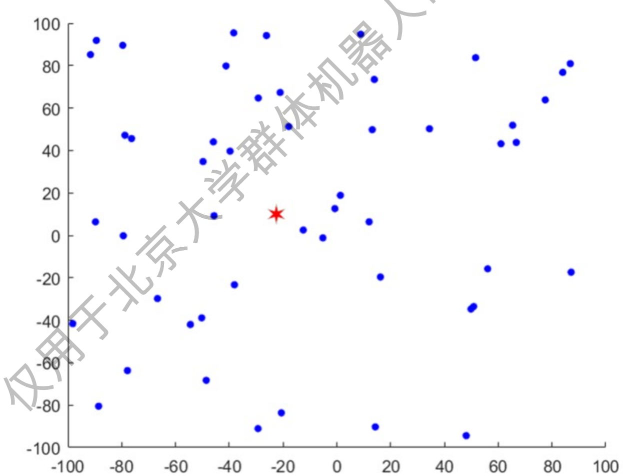
Particles flying：

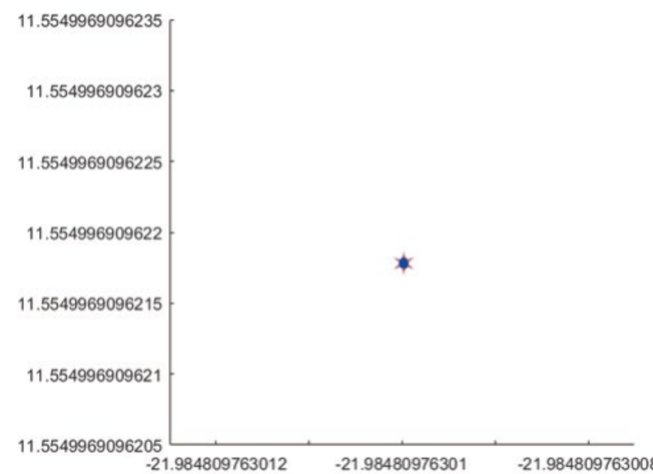
Environment:





Particle Swarm:

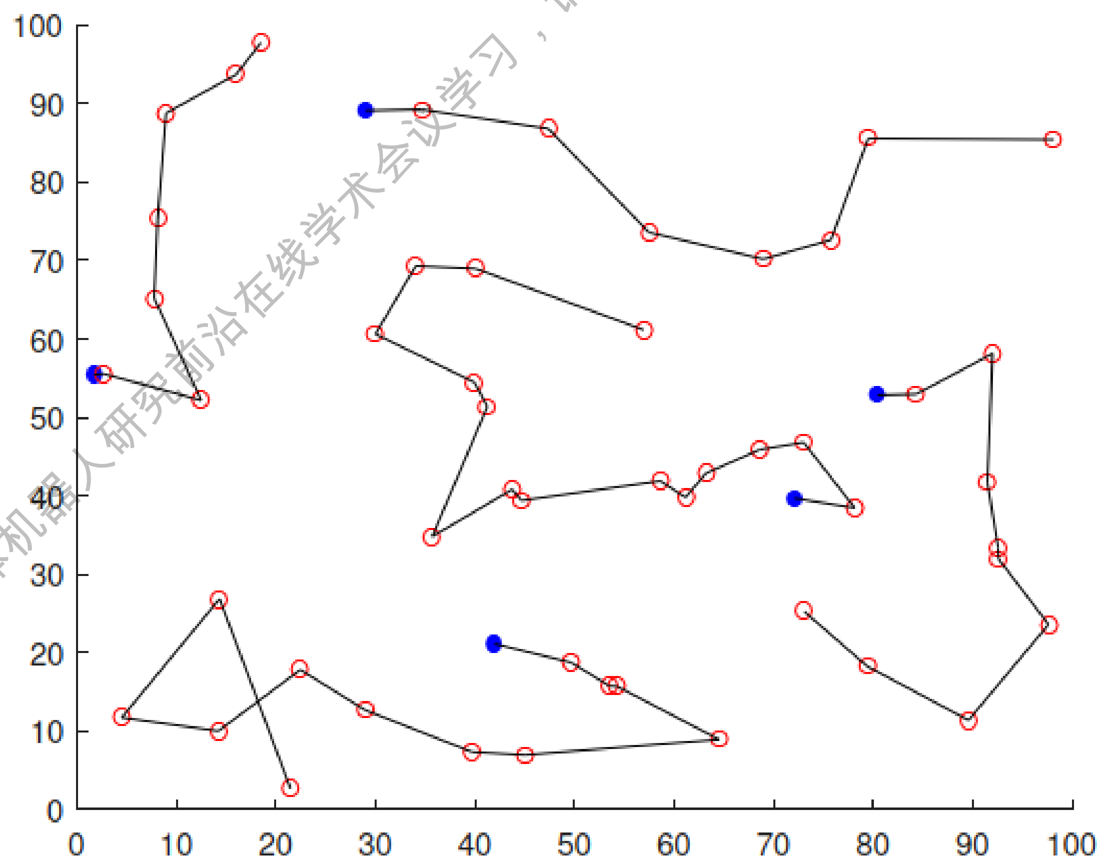




Experimental Results

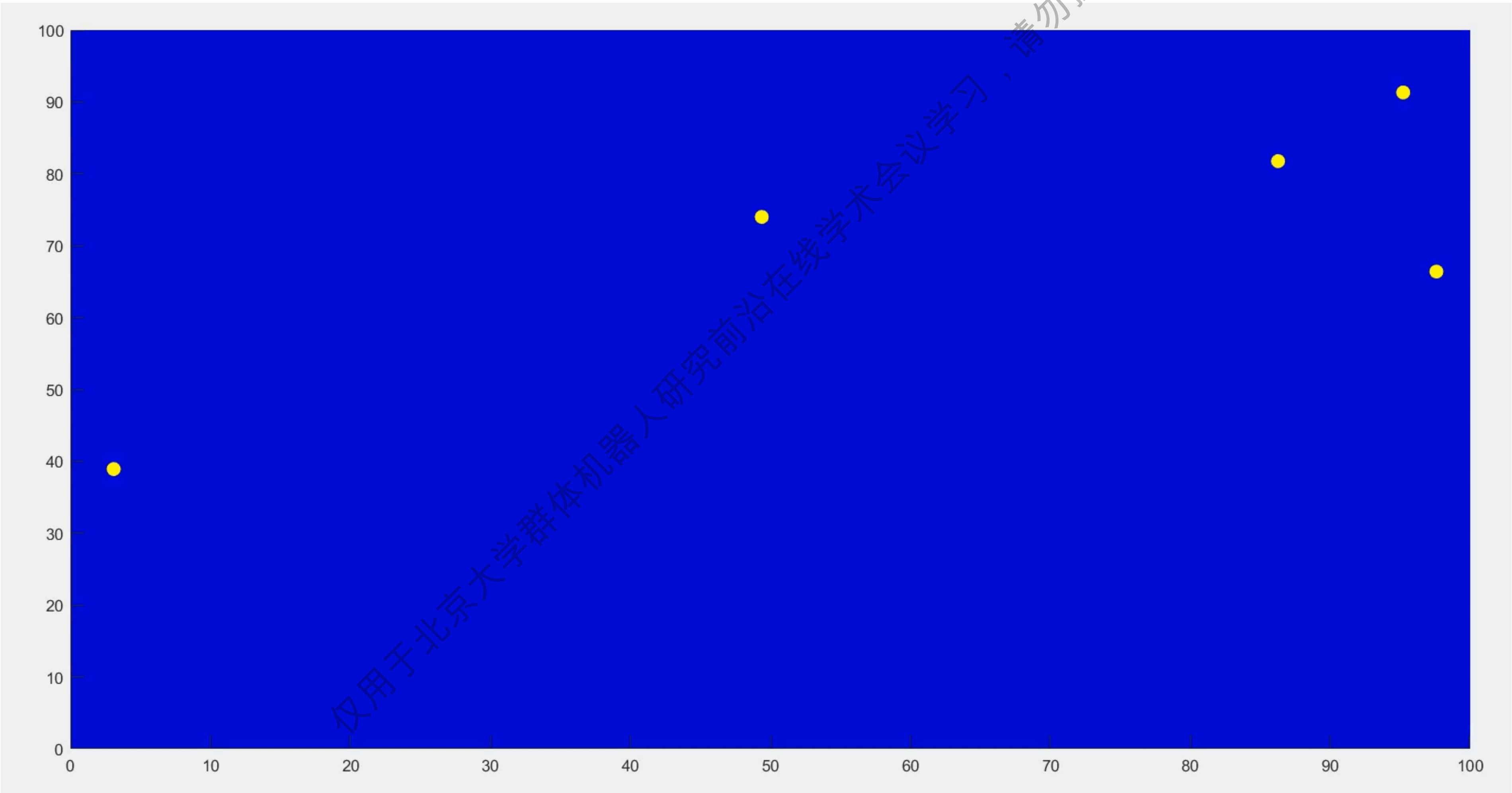
Path Planning for robot swarm in one generation:

- Robots
- Particle Positions



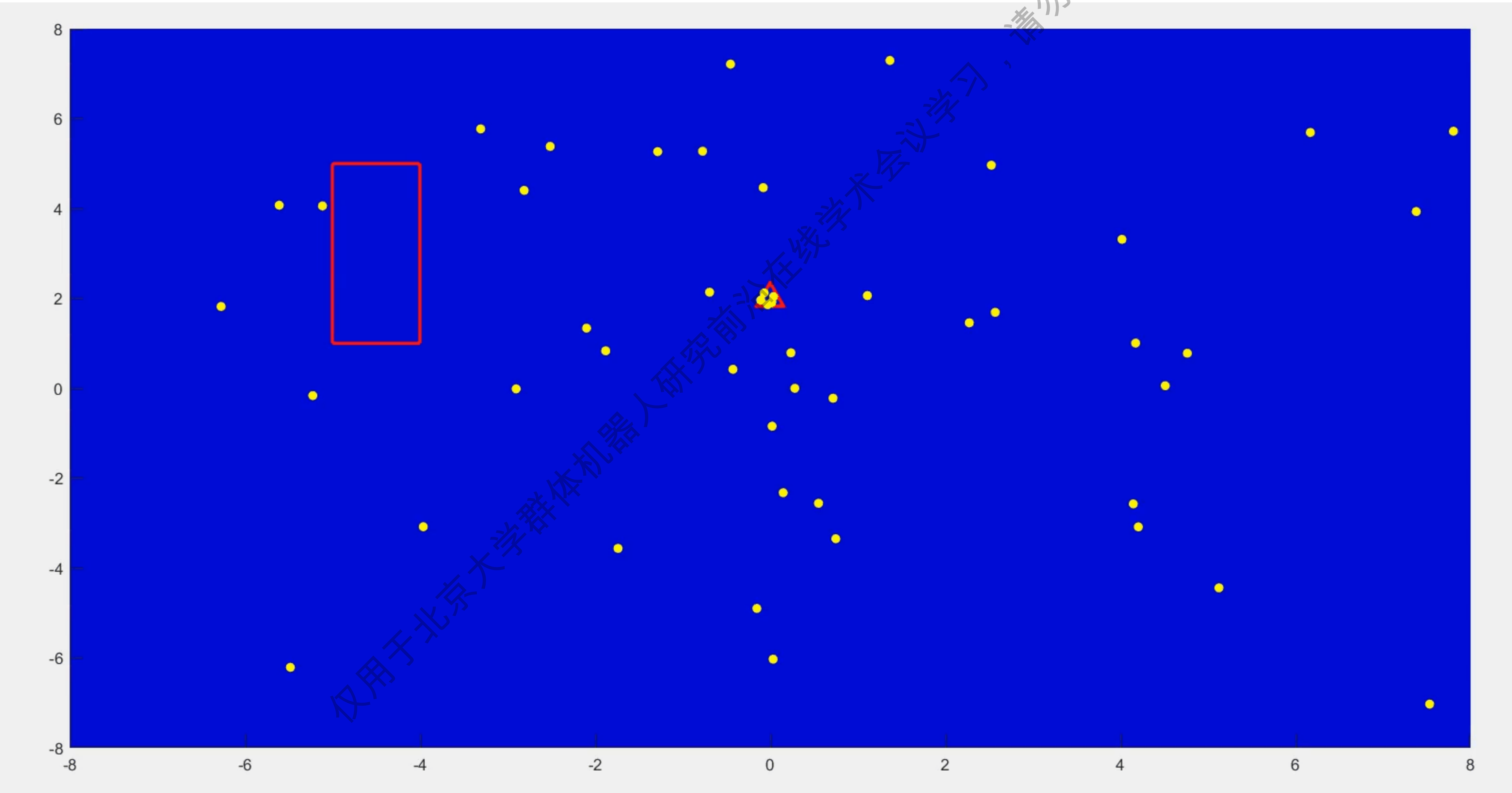
Experimental Results

Path Planning for robot swarm in one generation:



Experimental Results

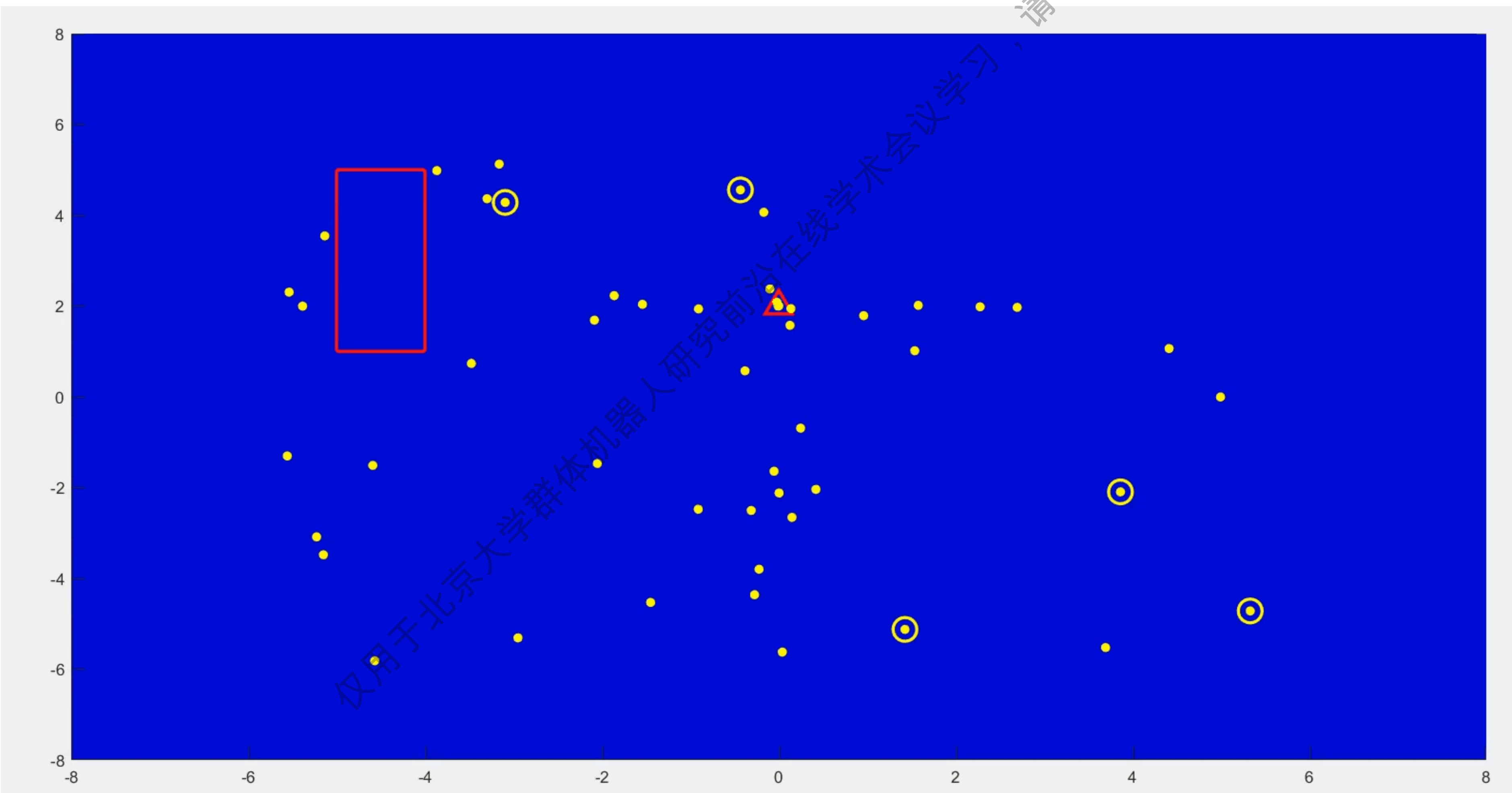
Convergence of particles：



Experimental Results

Robot Swarm Simulation:

- Particle
- ⊙ Robot



Experimental Results

Theoretical Experiments:

	Moving Distance		Makespan	
	m = n	m < n	m = n	m < n
SPSO	66.3%	82.3%	69.1%	77.6%
DEPSO	80.6%	72.9%	73.1%	70.9%

- **m: the number of robots.**
- **n: the number of particles.**
- **Our algorithm can be directly deployed to most PSO variants without modifying them.**

Conclusions

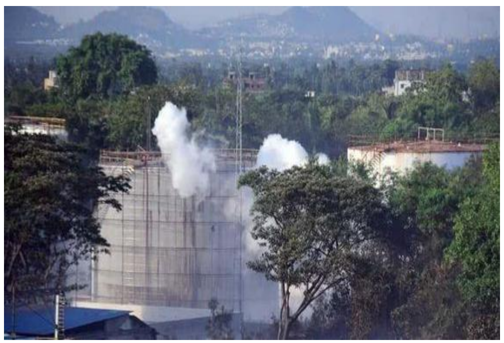
Advantages:

- ✓ The proposed algorithm can well control the mobile robot swarm to complete the source location problem.
- ✓ **The proposed algorithm can be directly deployed to most PSO variants to reduce moving distance and makespan without modifying them.**
- ✓ The system can uninterruptedly work even under the shortage of robots or in the case of unexpected failure of robots.
- ✓ When those sources lie in a dangerous environment or pose a risk to humans, our solution becomes more valuable.

Conclusions

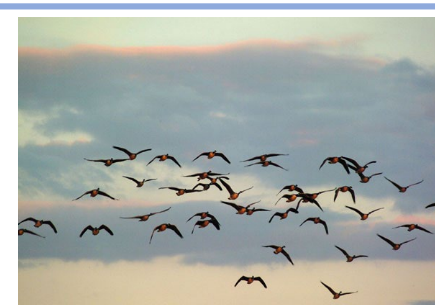
Extensions:

✓ Possible applications: Chemical spill investigation, Fire spot discover, Disaster zone rescue, etc.



✓ Suitable for other population-based methods: ABC, ACO, GSO, etc.



Thanks！