



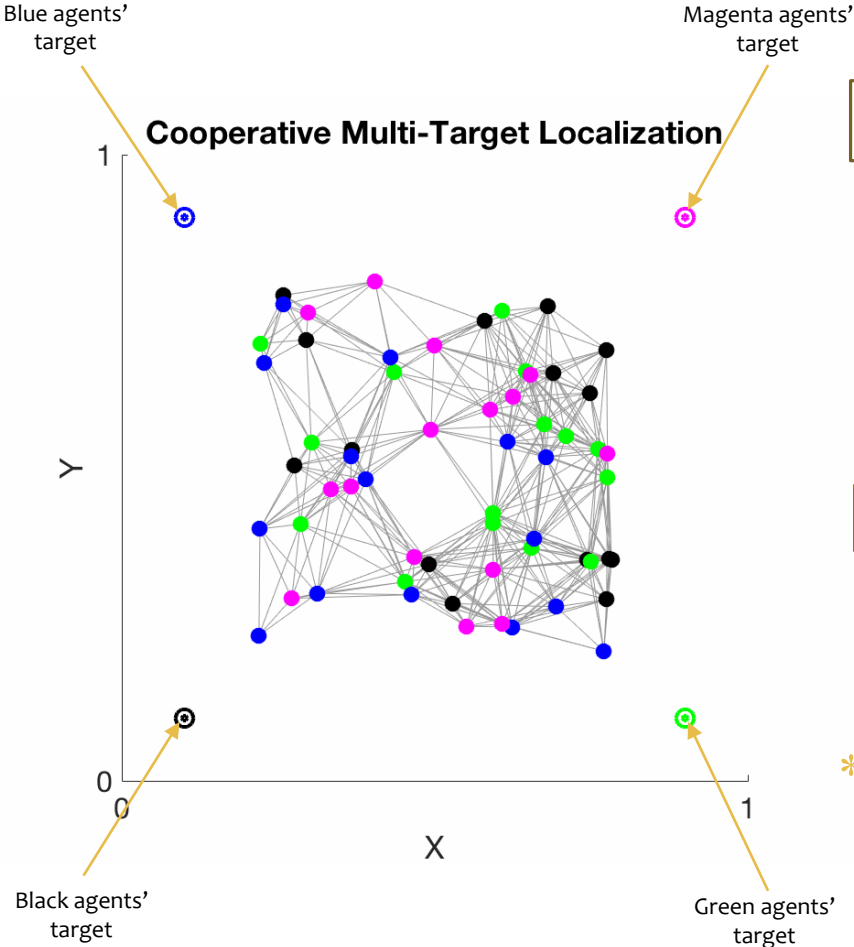
# Resilient Diffusion Least-Mean Squares over Adaptive Networks for Distributed Clustering in CPS

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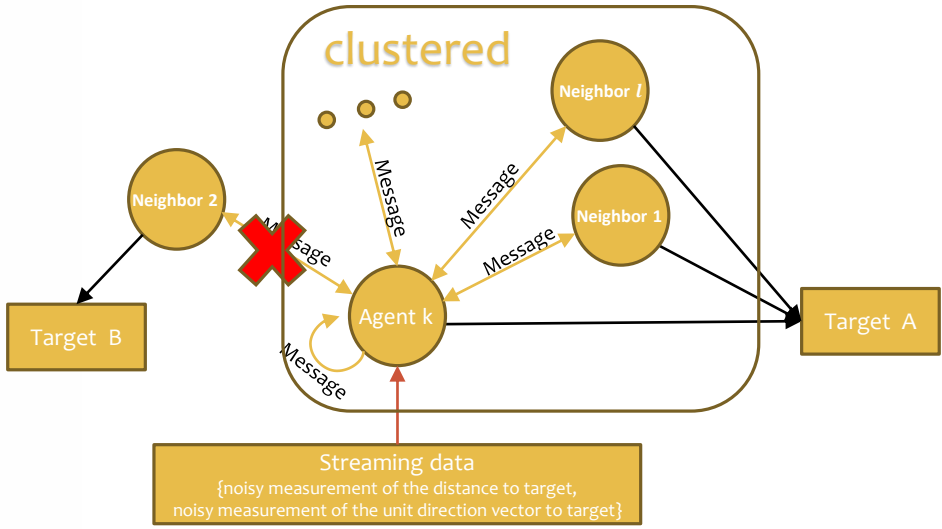
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# Motivating Application: Cooperative Multi-Target Localization



## Agent k's learning and clustering procedure



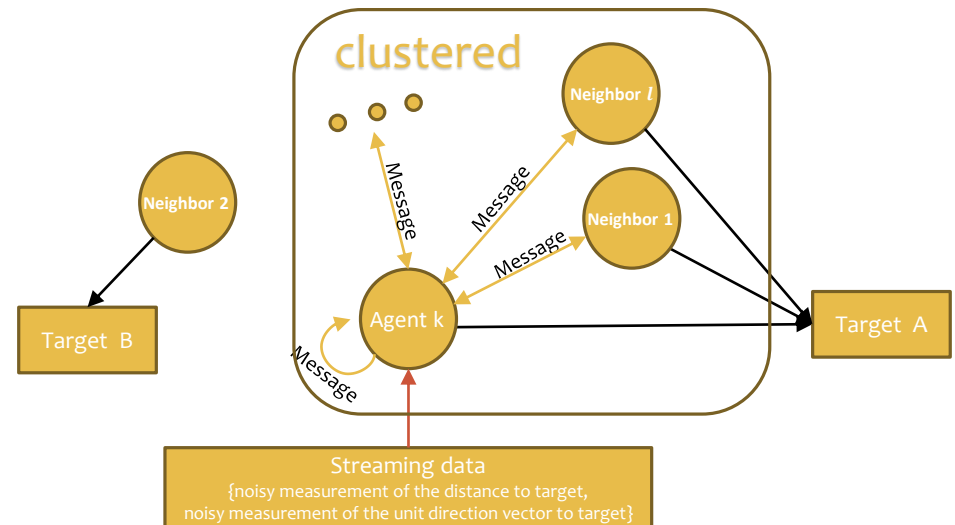
- \* Problem Formulation:
  - \* Distributed estimation
  - \* Multi-tasks network
  - \* Clustering for better estimation performance

# Motivating Application: Cooperative Multi-Target Localization

## \* Other Applications:

- \* Cooperative data mining
- \* Multi-task learning
- \* Distributed clustering
- \* Intrusion detection
- \* Static target localization
- \* Real-time learning, adaptation
  - \* Mobile target localization
- \* Spectrum sensing
- \* Speech enhancement
- \* Biological inspired design
  - \* Fish schooling
  - \* Bees swarming

## Agent k's learning and clustering procedure



## \* Problem Formulation:

- \* Distributed estimation (stationary/time-varying)
- \* Multi-tasks network
- \* Clustering for better estimation performance

# Diffusion Least-Mean Squares over Adaptive Networks for Distributed Clustering

**Algorithm 1** ATC diffusion strategy with adaptive combination weights

**Set**  $\gamma_{lk}^2(-1) = 0$  for all  $k = 1, 2, \dots, N$  and  $l \in N_k$

1: **for all**  $k = 1, 2, \dots, N, i \geq 0$  **do**

2:  $e_k(i) = \mathbf{d}_k(i) - \mathbf{w}_{k,i} \mathbf{w}_{k,i-1}$

3:  $\psi_{k,i} = \mathbf{w}_{k,i-1} + \mu_k \mathbf{u}_{k,i}^* e_k(i)$  } adaptation

4:  $\gamma_{lk}^2(i) = (1 - \nu_k) \gamma_{lk}^2(i-1) + \nu_k \|\psi_{l,i} - \mathbf{w}_{k,i-1}\|^2, l \in N_k$

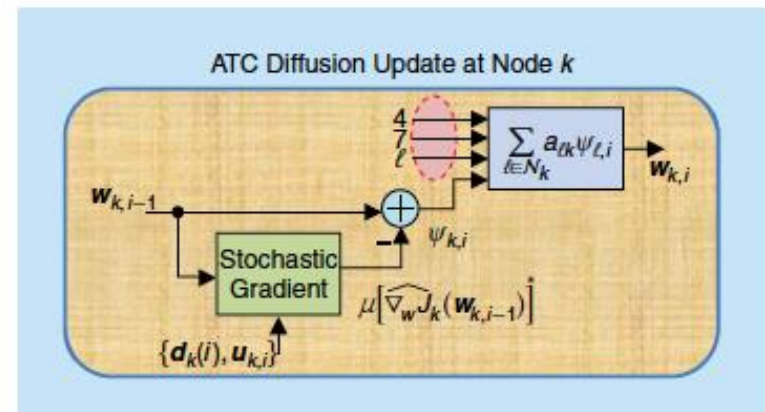
5:  $a_{lk}(i) = \frac{\gamma_{lk}^{-2}(i)}{\sum_{m \in N_k} \gamma_{mk}^{-2}(i)}, l \in N_k$  } combination

6:  $\mathbf{w}_{k,i} = \sum_{l \in N_k} a_{lk}(i) \psi_{l,i}$

7: **end for**

Communication message

weight metrics



Agents assign large weights to neighbors estimating a similar model with its own.

Ali H. Sayed, Sheng-Yuan Tu, Jianshu Chen, Xiaochuan Zhao, Zaid J. Towfic: **Diffusion Strategies for Adaptation and Learning over Networks: An Examination of Distributed Strategies and Network Behavior.** IEEE Signal Process. Mag. 30(3): 155-171 (2013)

# Diffusion Least-Mean Squares over Adaptive Networks for Distributed Clustering

**Q: Are these algorithms resilient to cyber-attacks?**

# Attack Objectives

## Assumption

Attacker knows the true model  $w_k^0$

Attacker does not know  $w_k^0$

Drive normal agents to converge to a point as far from  $w_k^0$  as possible.

Prolong the convergence time of the normal agents.

Drive normal agents to converge to a selected point  $w_k^a$

$$\max_{T_k} \|T_k\|$$

$$T \approx \frac{\ln\left(\frac{\epsilon N \cdot \text{MSD}}{1 - N \cdot \text{MSD}}\right)}{2 \ln(1 - \mu \text{Tr}(R_u)/M)}$$

$$\min_{w_k, T_k \in [w_{\min}, w_{\max}]} \|w_{k, T_k} - w_k^a\|$$

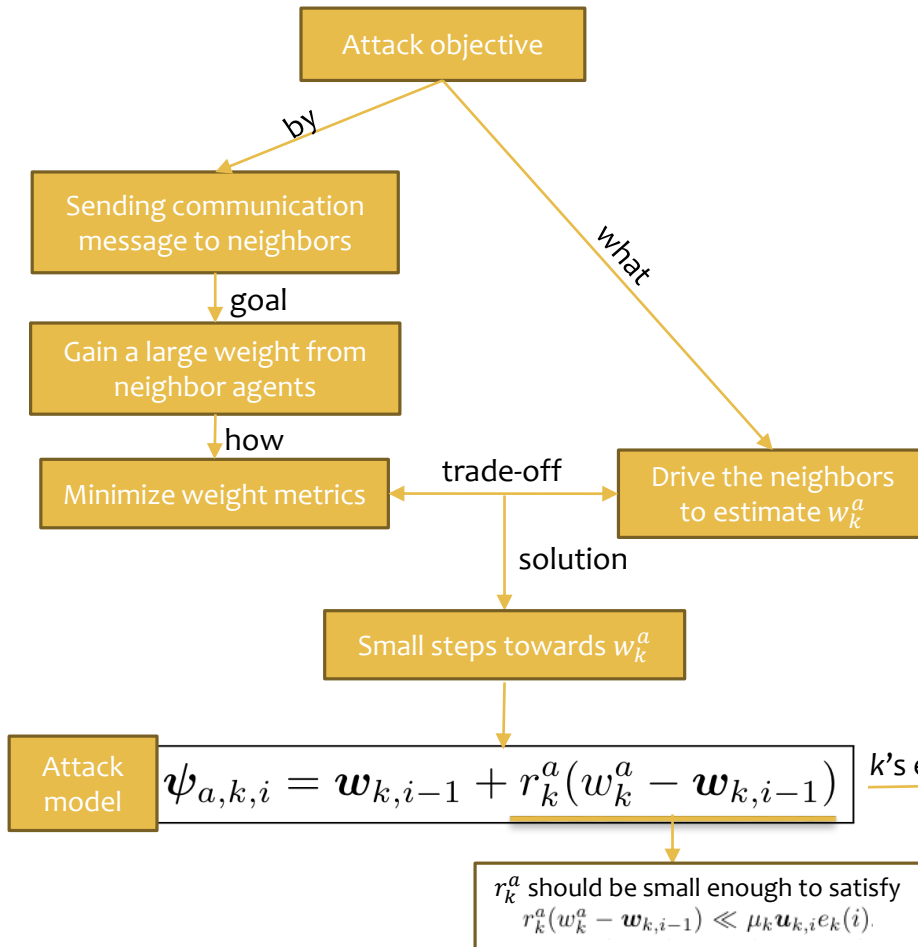
$$\max_{w_k, T_k \in [w_{\min}, w_{\max}]} \|w_k^0 - w_{k, T_k}\| \begin{cases} \max_{w_k^a \in [w_{\min}, w_{\max}]} \|w_k^0 - w_k^a\| \\ \min_{w_k, T_k \in [w_{\min}, w_{\max}]} \|w_{k, T_k} - w_k^a\| \end{cases}$$

$$w_k^a = \begin{cases} w_{\min}, & \text{if } \|w_{\min} - w_k^0\| \geq \|w_{\max} - w_k^0\| \\ w_{\max}, & \text{if } \|w_{\min} - w_k^0\| < \|w_{\max} - w_k^0\| \end{cases}$$

$$\min_{w_k, T_k \in [w_{\min}, w_{\max}]} \|w_{k, T_k} - w_k^a\|$$

- These objectives turn out to be represented in the same mathematical form.
- Under known  $w_k^0$ , attacker gets  $w_k^a$  by solving the maximization function.
- Under unknown  $w_k^0$ , attacker selects any  $w_k^a$ .
- For both known and unknown  $w_k^0$ , attacker needs to solve the minimization problem.
- That is, after entering stable state, attacker's neighbors should be estimating  $w_k^a$ .

# Attack Model



**Algorithm 1** ATC diffusion strategy with adaptive combination weights

**Set**  $\gamma_{lk}^2(-1) = 0$  for all  $k = 1, 2, \dots, N$  and  $l \in N_k$

- 1: **for all**  $k = 1, 2, \dots, N, i \geq 0$  **do**
- 2:  $e_k(i) = \mathbf{d}_k(i) - \mathbf{u}_{k,i} \mathbf{w}_{k,i-1}$
- 3:  $\psi_{k,i} = \mathbf{w}_{k,i-1} + \mu_k \mathbf{u}_{k,i}^* e_k(i)$
- 4:  $\gamma_{lk}^2(i) = (1 - \nu_k) \gamma_{lk}^2(i-1) + \nu_k \|\psi_{l,i} - \mathbf{w}_{k,i-1}\|^2, l \in N_k$
- 5:  $a_{lk}(i) = \frac{\gamma_{lk}^{-2}(i)}{\sum_{m \in N_k} \gamma_{mk}^{-2}(i)}, l \in N_k$
- 6:  $\mathbf{w}_{k,i} = \sum_{l \in N_k} a_{lk}(i) \psi_{l,i}$
- 7: **end for**

Communication message

weight metrics

# Attack Model

- \* How to get access to the neighbors' model  $w_{k,i}$ ?

$$w_{k,i-1} = \frac{\psi_{k,i} - \mu_k \mathbf{u}_{k,i}^* \mathbf{d}_k(i)}{1 - \mu_k \mathbf{u}_{k,i}^* \mathbf{u}_{k,i}}$$

- \* Therefore, to deduce  $w_{k,i-1}$ , the attacker needs the knowledge of  $\mu_k$  and streaming data  $\{\mathbf{d}_k(i), \mathbf{u}_{k,i}\}$ 
  - \*  $\mu_k$  can be obtained if it is uniform for all agents
  - \*  $\{\mathbf{d}_k(i), \mathbf{u}_{k,i}\}$  are transferred from data fusion to agents – can be intercepted by the attacker
  - \*  $\{\mathbf{d}_k(i), \mathbf{u}_{k,i}\}$  are sensed by agents – can be obtained by the attacker if it can get access to the sensor of the agents

Attack model

$$\psi_{a,k,i} = w_{k,i-1} + r_k^a (w_k^a - w_{k,i-1})$$

$r_k^a$  should be small enough to satisfy  $r_k^a (w_k^a - w_{k,i-1}) \ll \mu_k \mathbf{u}_{k,i} e_k(i)$ .

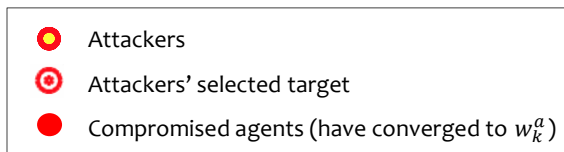
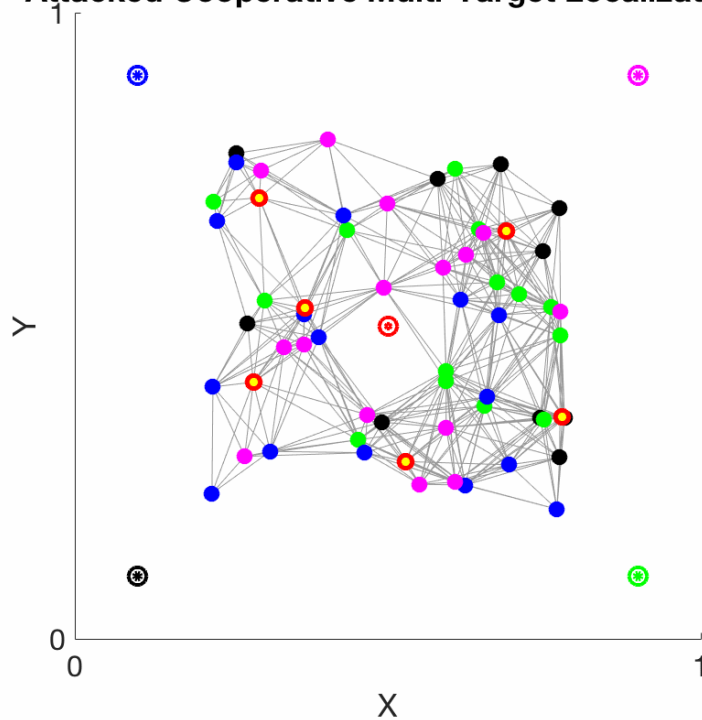
TABLE I: Streaming data representation in different problems

problem	$w_k^0$	$\mathbf{d}_k(i)$	$\mathbf{u}_{k,i}$
general distributed estimation / unsupervised clustering	estimated parameter	measurement received from data set	regression data received from data set
spectrum sensing / speech enhancement	signal transmitted by the source	signal received by agent $k$ from the source	frequency-dependent attenuation factors over $L$ frequency sample
target localization / biological design	target location	$\mathbf{d}_k(i) \triangleq \rho_k(i) + \mathbf{u}_{k,i} z_{k,i}$ , $\rho_k(i)$ - sensed (noisy) distance measurement between agent $k$ and target, $z_{k,i}$ - agent $k$ 's location	sensed (noisy) unit-norm direction vector pointing from the agent toward the target



# Select minimum set of agents to attack

## Attacked Cooperative Multi-Target Localization



### \* Attack model

$$\psi_{a,k,i} = \mathbf{w}_{k,i-1} + r_k^a (\mathbf{w}_k^a - \mathbf{w}_{k,i-1})$$

### \* Objective

- \* Attacker aims at compromising the entire network
- \* Select minimum set of agents to attack first
- \* Find minimum dominating set of the graph
- \* NP-complete and no efficient straight-forward solution!
- \* Attacker's way to approximate the solution

Algorithm	Greedy Algorithm
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- |    |   |
|----|---|
| 1: | $S := \emptyset;$   |
| 2: | <b>while</b> $\exists$ white nodes <b>do</b>              |
| 3: | choose $v \in \{x \mid w(x) = \max_{u \in V} \{w(u)\}\};$ |
| 4: | $S := S \cup \{v\};$                                      |
| 5: | <b>end while</b>  |

# Attack Detection

Agents will not be compromised if it processes data without cooperation

strategy

Process data by two means: 1. without cooperation 2. proposed diffusion strategy.  
When the estimation by diffusion strategy enters steady state, check the estimation difference between the two means.

Initialization:  $\text{alarm}(k) = 0$  for all  $k$ .

If the difference exceeds a certain threshold,  $\text{alarm}(k) = 1$ .

If  $\text{alarm}(k) = 1$ , agent  $k$  will not trust in the estimation by diffusion strategy.

use  $\|w_{\text{diff},k,i} - w_{\text{diff},k,i-1}\| < \Delta$  to approximate steady-state

Can be satisfied before steady-state because of noise fluctuation

False alarms

remove false alarms

If  $\text{alarm}(k) = 1$  and the difference is within a certain threshold,  $\text{alarm}(k) = 0$ .

# Attack Detection

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**Algorithm 2** Resilient ATC diffusion strategy with adaptive combination weights

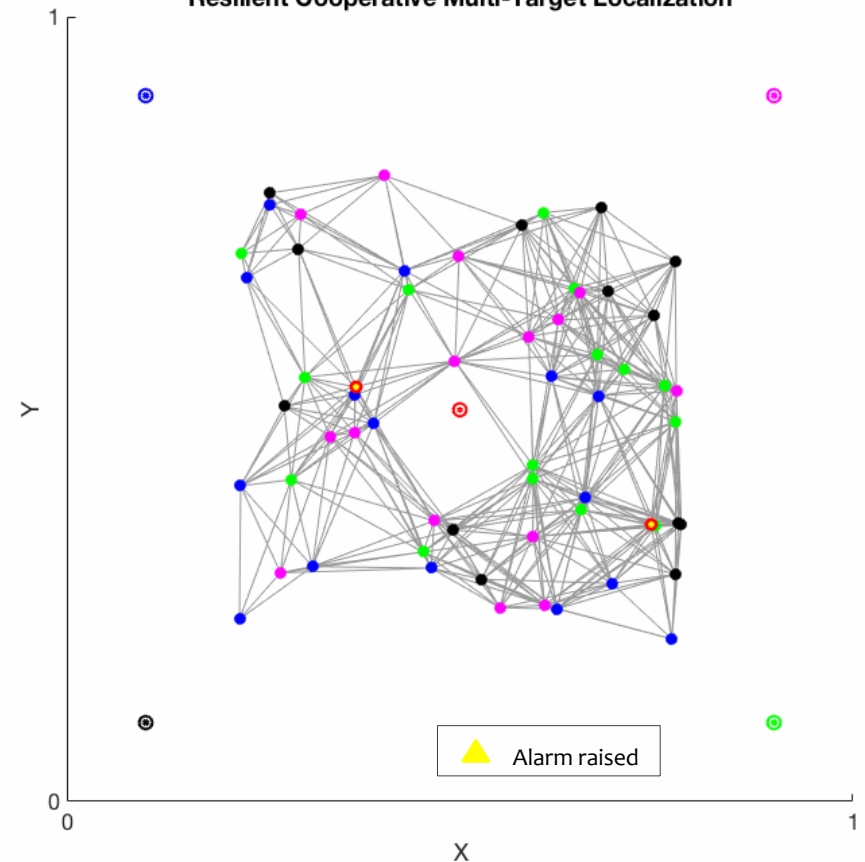
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Set  $\text{alarm}(k) = 0$ ,  $\gamma_{lk}^2(-1) = 0$  for all  $k = 1, 2, \dots, N$  and  $l \in N_k$

- 1: for all  $k = 1, 2, \dots, N, i \geq 0$  do
- 2:    $\boldsymbol{\psi}_{k,i} = \mathbf{w}_{\text{diff},k,i-1} + \mu_k \mathbf{u}_{k,i}^* (\mathbf{d}_k(i) - \mathbf{u}_{k,i} \mathbf{w}_{\text{diff},k,i-1})$
- 3:    $\gamma_{lk}^2(i) = (1 - \nu_k) \gamma_{lk}^2(i-1) + \nu_k \|\boldsymbol{\psi}_{l,i} - \mathbf{w}_{\text{diff},k,i-1}\|^2, l \in N_k$
- 4:    $a_{lk}(i) = \frac{\gamma_{lk}^{-2}(i)}{\sum_{m \in N_k} \gamma_{mk}^{-2}(i)}, l \in N_k$
- 5:    $\mathbf{w}_{\text{diff},k,i} = \sum_{l \in N_k} a_{lk}(i) \boldsymbol{\psi}_{l,i}$
- 6:    $\mathbf{w}_{\text{ncop},k,i} = \mathbf{w}_{\text{ncop},k,i-1} + \mu_k \mathbf{u}_{k,i}^* (\mathbf{d}_k(i) - \mathbf{u}_{k,i} \mathbf{w}_{\text{ncop},k,i-1})$   
    / \*\*\*\*\* detection section \*\*\*\*\* /
- 7:   if  $\|\mathbf{w}_{\text{diff},k,i} - \mathbf{w}_{\text{diff},k,i-1}\| < \Delta$
- 8:     if  $\text{alarm}(k) = 0$  and  $\|\mathbf{w}_{\text{ncop},k,i} - \mathbf{w}_{\text{diff},k,i}\| > \lambda$
- 9:        $\text{alarm}(k) = 1$
- 10:    elseif  $\text{alarm}(k) = 1$  and  $\|\mathbf{w}_{\text{ncop},k,i} - \mathbf{w}_{\text{diff},k,i}\| < \lambda$
- 11:      $\text{alarm}(k) = 0$
- 12: end for

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Resilient Cooperative Multi-Target Localization



# Future work

- \* Time-varying distributed estimation case
- \* Large noise variance case

Thank you!