Cooperative Situational Awareness of Multi-UAV Systems based on Improved D-S Evidence Theory

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Content

Applications of Multi-UAV Systems in Various Fields

Swarm Performance

Agriculture

Mars Exploration

Situational Awareness (SA)

[1] J. C. Taylor, D. W. Johnston, J. T. Ridge, W. Jenkins, A. Wakely, D. Hernandez, S. Robinson, J. McCombs, S. Eastman, and K. Dietz, "Drones in the coastal zone: Report of a regional workshop for the US southeast and caribbean," 2021.

Situational Awareness[2]

Definition

- Perception of the elements in the environment within a volume of time and space.

Goal

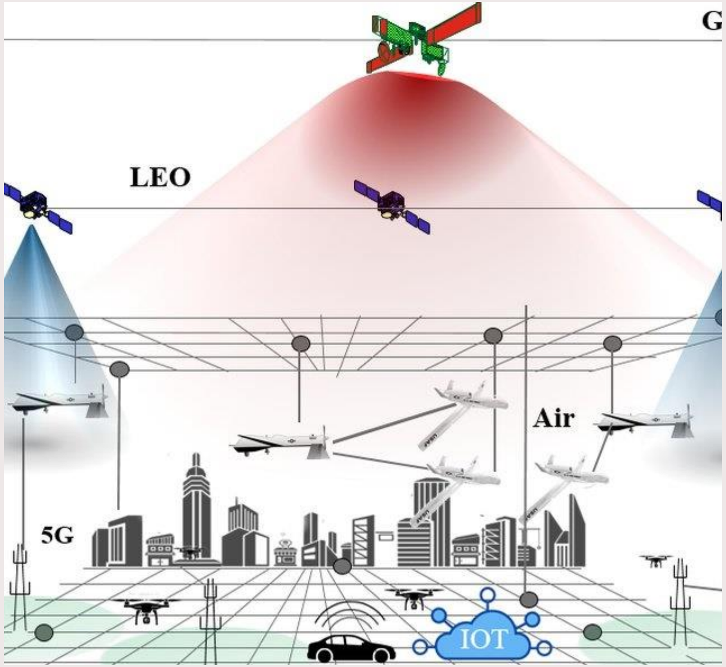
- Support further decision-making and improve efficiency.

Requirement

- The information obtained by all UAVs should be as consistent as possible with the true information.

Current Situation

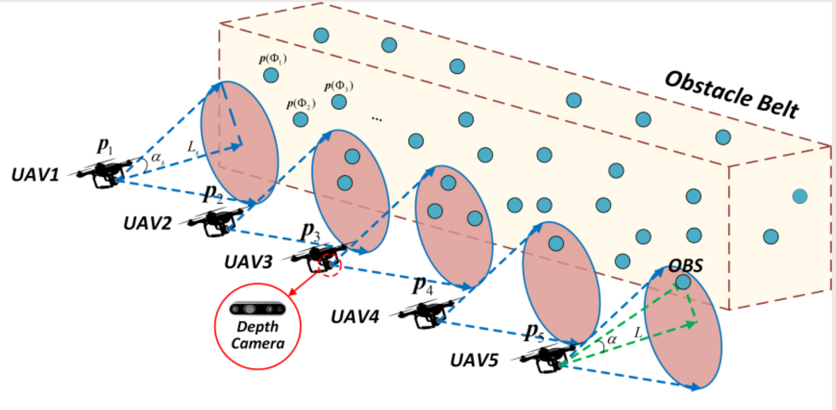
- Single information source cannot satisfy the demand.
- Disturbance, uncertainty…
- Extend SA to cooperative field.



Situation awareness of multi-agent systems[3].

[2] M. R. Endsley, "Toward a theory of situation awareness in dynamic systems," Human factors, vol. 37, no. 1, pp. 32–64, 1995.
[3] N. Hosseini, H. Jamal, J. Haque, T. Magesacher, and D. W. Matolak, "UAV command and control, navigation and surveillance: A review of potential 5g and satellite systems," in 2019 IEEE Aerospace Conference. IEEE, 2019, pp. 1–10.

Scenario Assumption



Scenario assumption of multi-UAV system detection.

Challenge 1

- How to incorporate the information detected by each UAV in the system?

Challenge 2

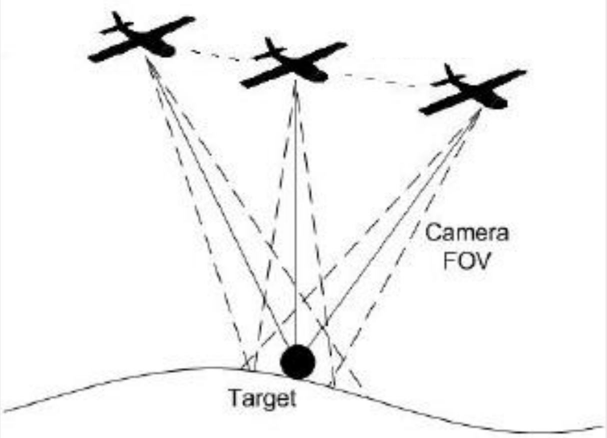
- How to overcome the effects of detection uncertainty and limited capability of airborne sensors?

- **A multi-UAV system detects a 3D obstacle belt with distributed obstacles.**
- **Detection uncertainty occurs during the perception, especially when obstacle deviates.**
- **Each UAV carries a limited-capability depth camera to detect obstacles within a perception range.**

High-Conflict Situation

BPA of four common paradoxes.

Paradoxes	Evidence	A	B	C	D	E
		Propositions				
Complete conflict paradox (1)	m_1	1	0	0	\	\
	m_2	0	1	0	\	\
	m_3	0.8	0.1	0.1	\	\
	m_4	0.8	0.1	0.1	\	\
0 trust paradox (2)	m_1	0.5	0.2	0.3	\	\
	m_2	0.5	0.2	0.3	\	\
	m_3	0	0.9	0.1	\	\
	m_4	0.5	0.2	0.3	\	\
1 trust paradox (3)	m_1	0.9	0.1	0	\	\
	m_2	0	0.1	0.9	\	\
	m_3	0.1	0.15	0.75	\	\
	m_4	0.1	0.15	0.75	\	\
High conflict paradox (4)	m_1	0.7	0.1	0.1	0	0.1
	m_2	0	0.5	0.2	0.1	0.2
	m_3	0.6	0.1	0.15	0	0.15
	m_4	0.55	0.1	0.1	0.15	0.1
	m_5	0.6	0.1	0.2	0	0.1



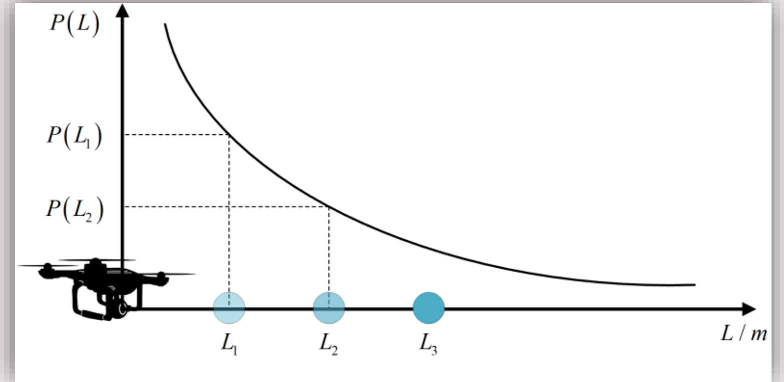
Traditional D-S evidence theory is unable to deal with high-conflict situations!

Challenge 3

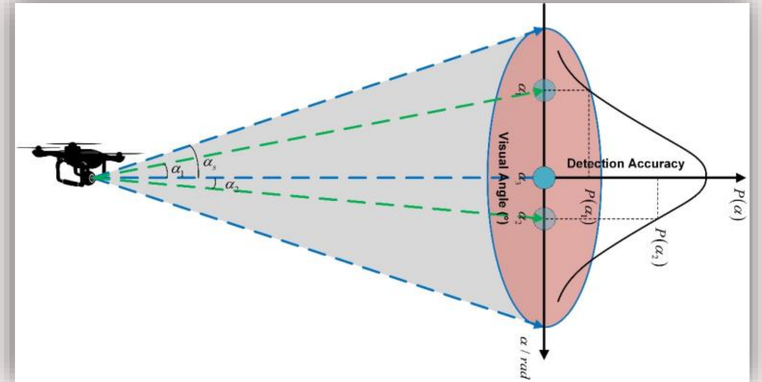
- How to process the contradictory information under high-conflict paradoxes?

TU/e

Uncertainty Modeling



Relationship between detection accuracy and visual distance.



Relationship between detection accuracy and visual angle.

$$f(L) = \lambda e^{-\lambda L}$$

$$f(\alpha) = \frac{1}{\sigma\sqrt{2\pi}} e^{\frac{-\alpha^2}{2\sigma^2}}$$

Detection Accuracy

$$P_A(L,\alpha) = \sqrt{2\pi}\,\frac{\sigma}{\lambda} \cdot \boxed{\lambda e^{-\lambda L}} \cdot \frac{\boxed{e^{-\frac{\alpha^2}{2\sigma^2}}}}{\sigma\sqrt{2\pi}} \cdot \delta(L,\alpha) = e^{-\frac{\alpha^2}{2\sigma^2}-\lambda L} \cdot \boxed{\delta(L,\alpha)}$$

Step Function

Framework of D-S Evidence Theory [3]

It can deal with uncertainty to some degree.

- **Discernment Frame**

A set Θ consisting of independent, complete, and exclusive elements $\Phi_1, \Phi_2, \cdots, \Phi_n$.

Its power set 2^Θ can be expressed as

$$2^\Theta = \{\varnothing, \{\Phi_1\}, \{\Phi_2\}, \cdots, \{\Phi_n\}, \{\Phi_1 \cup \Phi_2\}, \{\Phi_1 \cup \Phi_3\}, \cdots, \Theta\}$$

- **Basic Probability Assignment**

Assume each obstacle Φ_i maps to a function $m(\Phi_i)$ $(m(\Phi_i) \in [0,1])$. If $m(\Phi)$ satisfies

$$m(\varnothing) = 0; m(\Phi) \geq 0; \sum_{\Phi = 2^\Theta} m(\Phi) = 1,$$

then m is qualified as a BPA on Θ.

- **D-S Combination Rule**

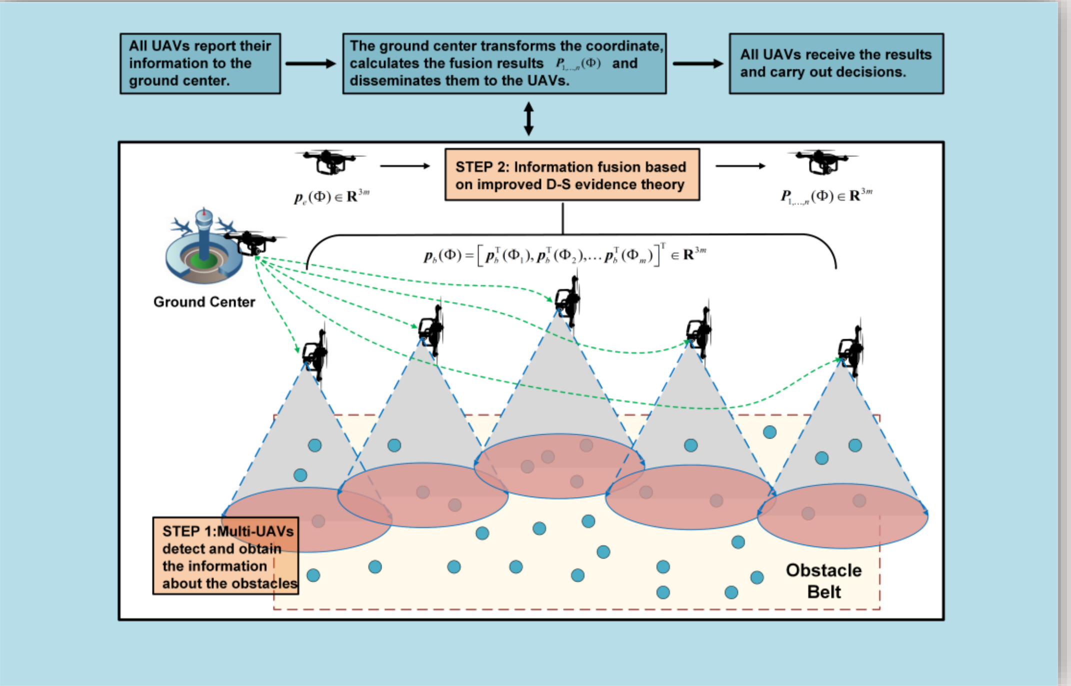
After determining the discernment frame, multiple independent sets of BPAs can be fused through

$$\begin{cases} \forall \Phi \subset \Theta, \Phi \neq \varnothing, \Phi_1, \Phi_2, \ldots, \Phi_n \subset \Theta \\ m(\Phi) = k \displaystyle\sum_{\substack{\Phi_1, \Phi_2, \ldots, \Phi_n \subset \Theta \\ \Phi_1 \cap \Phi_2 \cap, \ldots \Phi_n = \Phi}} m_1(\Phi_1) m_2(\Phi_2) \ldots m_n(\Phi_n) \\ k = \left(1 - \displaystyle\sum_{\substack{\Phi_1, \Phi_2, \ldots, \Phi_n \subset \Theta \\ \Phi_1 \cap \Phi_2 \cap \ldots \cap \Phi_n = \varnothing}} m_1(\Phi_1) m_2(\Phi_2) \ldots m_n(\Phi_n) \right)^{-1} \end{cases}$$

where k is the conflict coefficient.

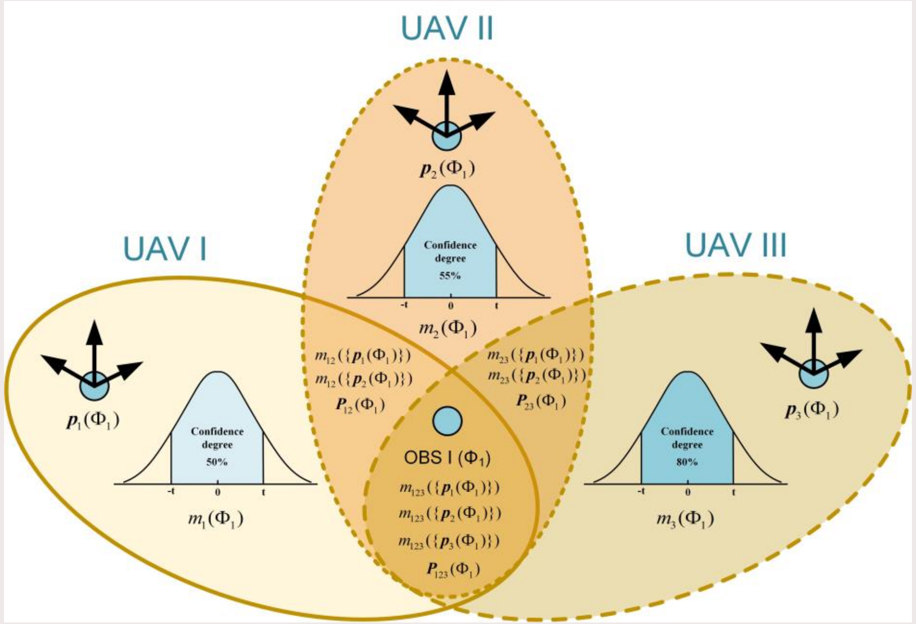
[3] A. P. Dempster, Upper and lower probabilities induced by a multivalued mapping, in: Classic works of the Dempster-Shafer theory of belief functions, Springer, 2008, pp. 57–72.

Task Flow



- **Step 1:** Multi-UAV system detects and obtains the coordinate and accuracy of obstacles.
- **Step 2:** Coordinate transformation and information fusion based on D-S evidence theory.
- **Step 3:** All UAVs receive the fusion results and achieve the cooperative situational awareness.

CSA Among Multiple UAVs



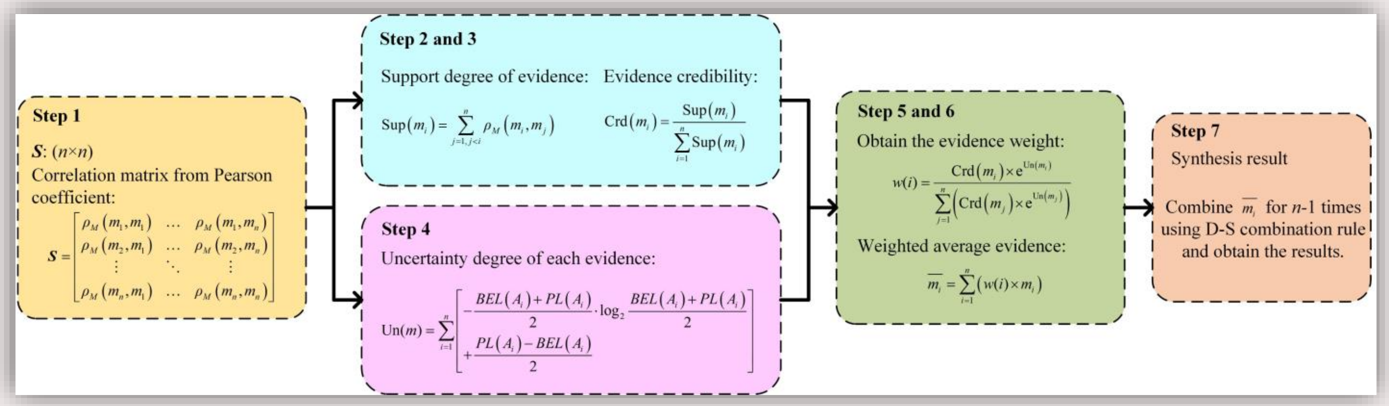
Information fusion among multiple UAVs.

- The information fusion among UAV I, II and III on OBS I is taken as the example.

- Each UAV can detect and obtain the position of OBS I with different accuracy.

- The fused position and accuracy of obstacles are calculated.

Method Improvements Towards High-Conflict Situations



The flow chart of improved evidence combination method.

Improvement 1

- Introduction of Pearson coefficient to measure the correlation.

Improvement 2

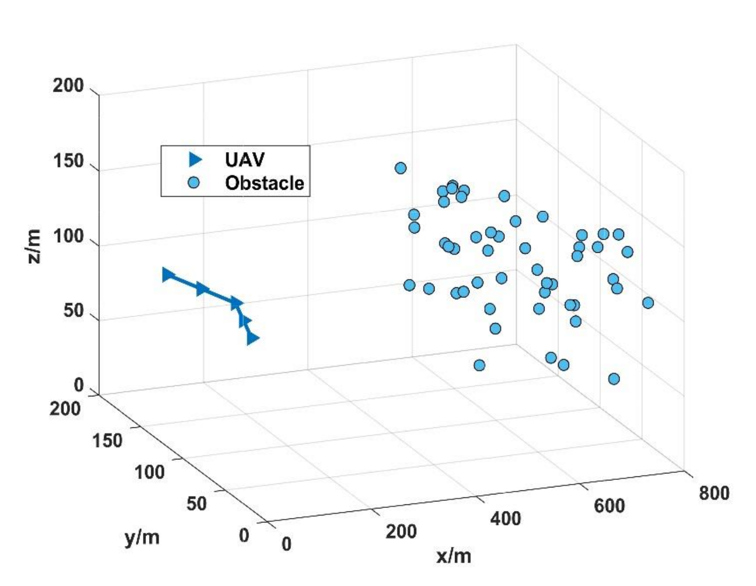
- Comprehensive consideration of evidence credibility and uncertainty.

Improvement 3

- Weighted average the original evidence to obtain the fusion results.

Simulation Under a Fixed Formation

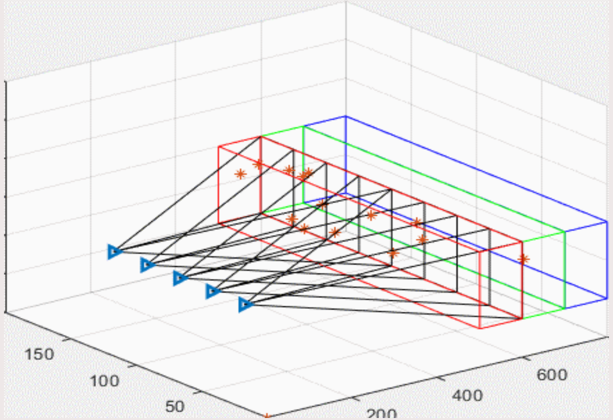
- Verify the effectiveness of the CSA method.



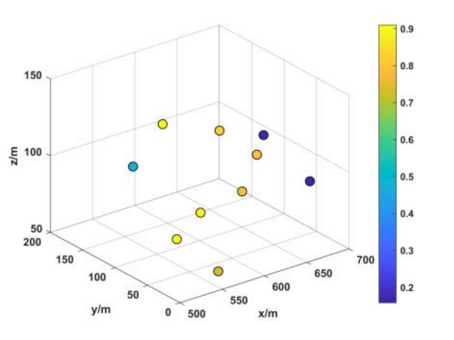
Distribution of UAVs and obstacles under a certain formation shape.

Parameter setting.

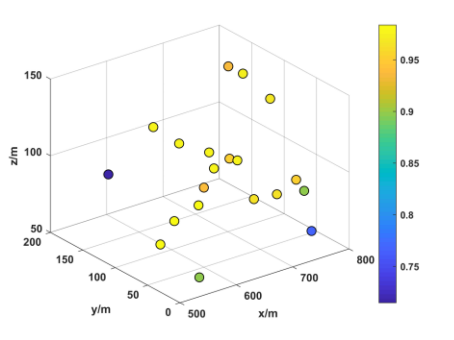
Item	Parameter	item	Parameter
Obstacle space	300 m × 200 m × 100 m	Δt	1 s
n_{OBS}	From 20 to 100	λ	0.6
n_{UAV}	5	σ	1
$\boldsymbol{v}_i = [v_i^x, v_i^y, v_i^z]^{\mathrm{T}}$	$[20, 0, 0]^{\mathrm{T}}$m/s	L_s	$0 \sim 550$ m
Velocity direction	Positive X axis	θ_s	$-45° \sim +45°$



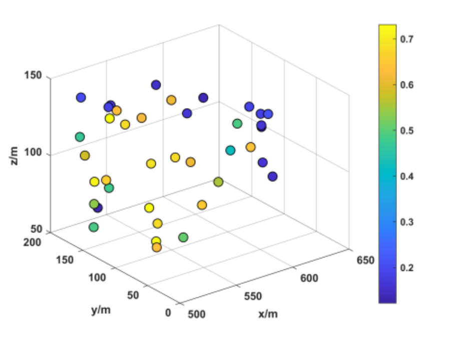
Simulation Under a Fixed Formation



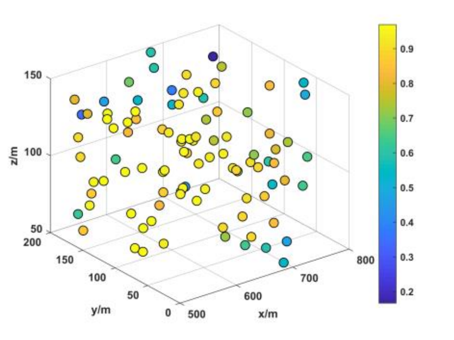
SA result (n_{OBS}=20)



CSA result (n_{OBS}=20)



SA result (n_{OBS}=100)



CSA result (n_{OBS}=100)

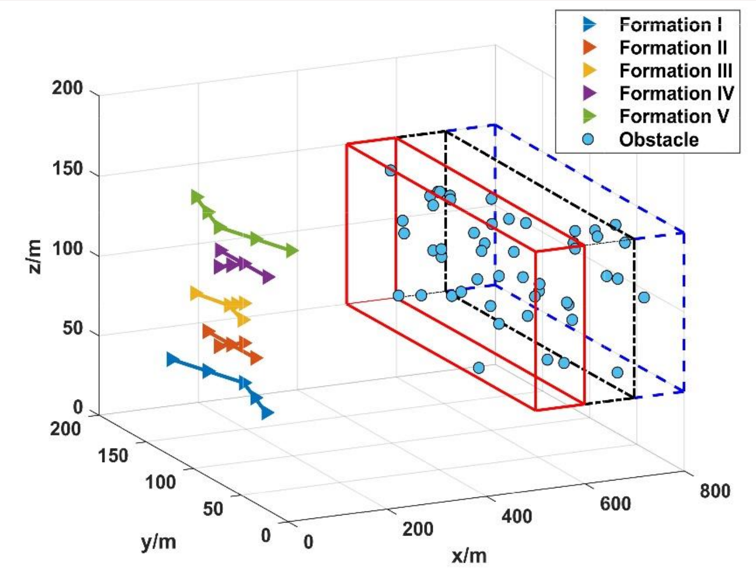
Comparison result between SA and CSA.

n_{OBS}	Method	Detected obstacles	Average detection accuracy
20	SA	10	33.18%
	CSA	**20**	**93.85%**
40	SA	23	41.25%
	CSA	**40**	**90.87%**
60	SA	38	39.47%
	CSA	**60**	**87.33%**
80	SA	42	32.41%
	CSA	**79**	**82.66%**
100	SA	39	17.52%
	CSA	**98**	**79.09%**

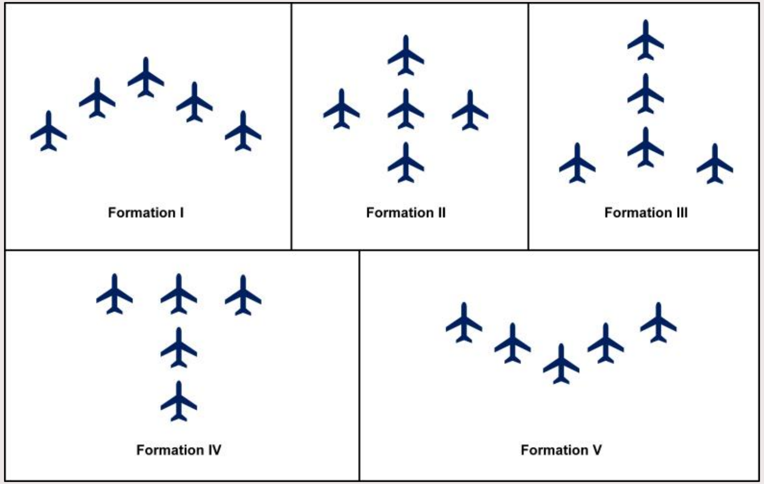
- **The number of detected obstacles doubles.**
- **The average detection accuracy increases by 40%-50%.**

Simulation Under Flexible Formation Shapes

- Verify the scalability of the CSA method.

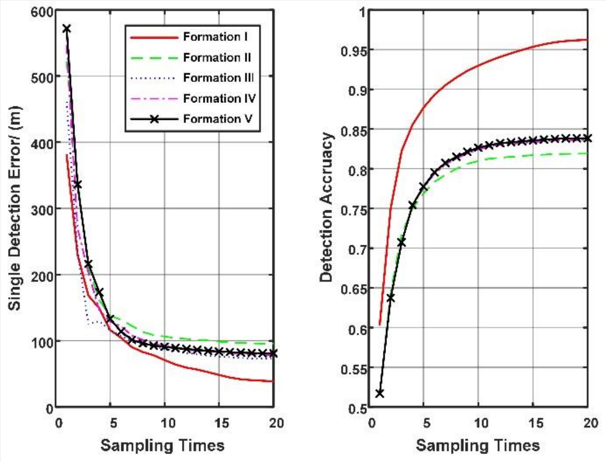


Distribution of UAVs and obstacles under flexible formation shapes.

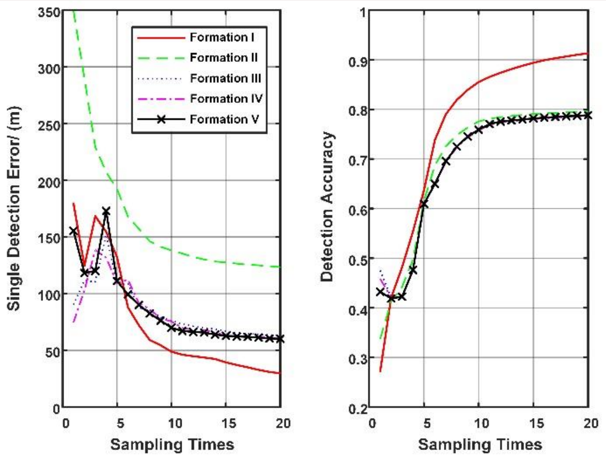


- **Obstacle number is fixed.**
- **Different formation shapes are applied.**

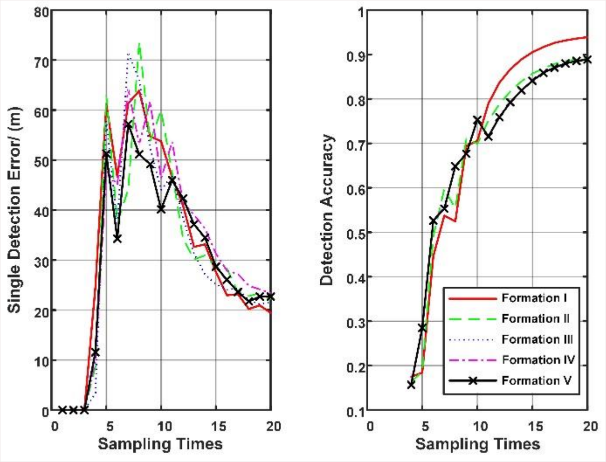
Simulation Under Flexible Formation Shapes



Fusion result of Area I.



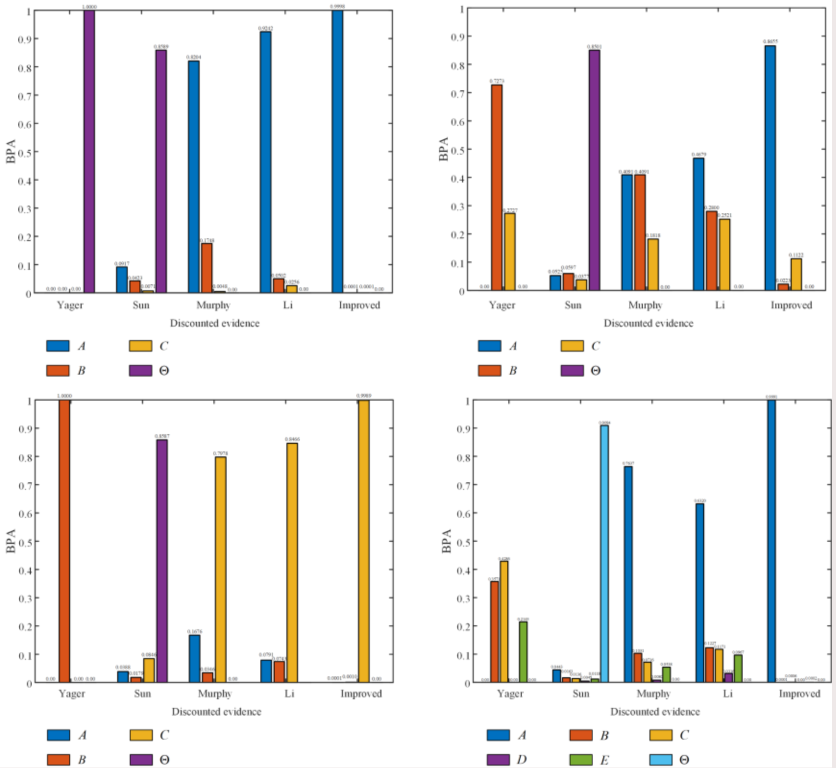
Fusion result of Area II.



Fusion result of Area III.

- All formations can complete the detection of the three areas with low error and high accuracy.
- Formation I achieves the optimal detection performance, reaching 96.58% accuracy.

Comparison Between the Improved Algorithm and Existing Methods



Paradoxes	Methods	Propositions					
		A	*B*	*C*	*D*	*E*	*F*
(1)	*Yager*	0	0	0	\	\	1
	Sun	0.0917	0.0423	0.0071	\	\	0.8589
	Murphy	0.8204	0.1748	0.0048	\	\	0
	Li	0.9242	0.0502	0.0256	\	\	0
	Improved	**0.9998**	0.0001	0.0001	\	\	0
(2)	*Yager*	0	0.7273	0.2727	\	\	0
	Sun	0.0525	0.0597	0.0377	\	\	0.8501
	Murphy	0.4091	0.4091	0.1818	\	\	0
	Li	0.4679	0.2800	0.2521	\	\	0
	Improved	**0.8655**	0.0223	0.1122	\	\	0
(3)	*Yager*	0	1	0	\	\	0
	Sun	0.0388	0.0179	0.0846	\	\	0.8587
	Murphy	0.1676	0.0346	0.7978	\	\	0
	Li	0.0791	0.0743	0.8466	\	\	0
	Improved	0.0001	0.0010	**0.9989**	\	\	0
(4)	*Yager*	0	0.3571	0.4286	0	0.2143	0
	Sun	0.0443	0.0163	0.0136	0.0045	0.0118	0.9094
	Murphy	0.7637	0.1031	0.0716	0.0080	0.0538	0
	Li	0.6320	0.1227	0.1171	0.0316	0.0967	0
	Improved	**0.9991**	0.0001	0.0006	0	0.0002	0

Conclusions

- Investigating the cooperative detection problem of multi-UAV systems in 3D space.
- Modeling and characterizing the detection and sensor uncertainties.
- Modifying the traditional D-S evidence theory to treat high-conflict situations.
- Demonstrating the superiority of the CSA method through numerical simulations.

Future Work

- The consideration of the heterogeneous multi-sensor fusion.
- The consideration of further improvement of information fusion method (e.g., Evidential Reasoning, ER).

Thanks for Listening!