Cooperative Situation Awareness of Multi-UAVs Based on Multi-sensor Information Fusion

Zirui Liao[1,2,3], Shaoping Wang[1,2], Jian Shi[1,2](✉), Zhenkun Li[1,2], and Muhammad Baber Sial[1,2]

[1] School of Automation Science and Electrical Engineering, Beihang University, Beijing 100191, China
{by2003110,lizhenkun,babersial}@buaa.edu.cn, shaopingwang@vip.sina.com, shijian123@sina.com

[2] Beijing Advanced Innovation Center for Big-Data Based Precision Medicine, Beihang University, Beijing 100191, China

[3] Shenyuan Honors College, Beihang University, Beijing 100191, China

Abstract. In recent years, situation awareness has been an essential research subject in the field of low altitude combat. However, previous work mainly focused on single unmanned aerial vehicle (UAV) detection, while it may obtain inaccurate information about the environment due to the limited detection ability and uncertainty of single airborne sensor. By contrast, this paper considers the cooperative detection of multi-UAVs and proposes a cooperative situation awareness method on the basis of multi-sensor information fusion. Firstly, obstacle information is detected and obtained by multiple airborne sensors considering the sensors' uncertainty. Subsequently, D-S evidence theory is introduced to conduct the information fusion of obstacle with high confidence and more accurate obstacle coordinates are obtained. Next, the simulations of information fusion are conducted under fixed and flexible formations. Eventually, numerical results verify the validity of the proposed information fusion method, which can perceive the situation more accurately and reach at most 96.58% degree of confidence in a specific formation, thus achieving a precise cooperative situation awareness.

Keywords: Multi-UAVs · Cooperative situation awareness · Information fusion · D-S evidence theory

1 Introduction

Situation awareness (SA) refers to an environment-based, dynamic and overall ability to understand security risks [1], which is also an approach to improve the ability to discover, identify, understand, analyze, respond, and deal with security threats from a global perspective based on large amount of information [2]. It is ultimately for decision-making [3] and the landing of security capabilities [4]. Moreover, as a key factor of multi-UAV formation [5, 6] cooperative operation, the cooperative situation awareness of the swarm has also attracted extensive attention in relevant fields. Swarm cooperative situation awareness requires that the information obtained by all UAVs should be as consistent

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as possible with real information, while the analysis of task-related situations should be highly consistent. However, the strong uncertainty of the combat environment can easily lead to large differences in the situational awareness of the individuals. Therefore, the formation is supposed to reduce or eliminate the impact of uncertainty through the interaction of information, so as to improve the detection ability, obtain accurate environment information and achieve a precise global situation awareness. And information fusion is extremely appropriate to solve this problem.

Information fusion technology is a rapidly developing discipline and has been applied to various scenarios, such as situation awareness [7–9], classification [10], intelligent control [11] and so on [12, 13]. Over the last decades, Significant research has been conducted on information fusion, especially in its sub-project: multi-sensor information fusion. It is an emerging research field with broad application prospects. Its basic principle is the same as the human brain that comprehensively processes events under multiple environmental factors. The information obtained by various sensors are processed by multi-level, multi-temporal and spatial information complementarity and optimization, and finally produce a unified judgment result of the target environment. Theoretical multi-sensor information fusion methods include weighted average method, Kalman filter method [14], Bayesian estimation method [15], Dempster Shafer (D-S) evidence theory [16–18], fuzzy set theory [19], etc. Nevertheless, the uncertainty caused by sensor aging and interference of other factors in the process of data acquisition often leads to abnormal information. Bayesian estimation method and D-S evidence theory are two most proper approaches to deal with this kind of uncertainty. However, Bayesian estimation method needs to use the previous a priori probability to get a new probability, which is not applicable in many cases [20]. D-S evidence theory is able fuse uncertain problems when the prior probability is unknown and use the basic probability assignment to represent the probability of uncertain problems, which indicates a superior fusion performance. Due to its advantages, D-S evidence theory has been employed in various areas to solve related problems. In [21], D-S evidence theory is taken in diagnosing engine faults, in which the information quality is also considered. In [22], a novel approach based on the framework of D-S evidence theory is presented aiming at obtaining more reasonable information fusion results. Besides, the method is also adequate in handling challenges like decision-making [23], classification [24], sensor information fusion [25], and so on. Consider its excellent performance at dealing with sensor uncertainty, D-S evidence theory is adopted to accomplish the cooperative situation awareness of multi-UAVs in our research.

The other sections of the paper are arranged as follows: the fusion scenario and related problems are presented in Sect. 2. In Sect. 3, the fundamental framework of D-S evidence theory is introduced and the information fusion process among different UAVs and moments are elaborated. A case study of information fusion and numerical results of cooperative situation awareness under fixed and flexible formations are displayed in Sect. 4. Finally, Sect. 5 draws the related conclusions and prospects the potential future work of multi-UAVs' cooperative situation awareness.

2 Problem Statement

Consider a specific scenario that an UAV formation composed of one master and four slaves encounters an unknown obstacle belt when moving along the expected path shown in Fig. 1. It is assumed that the airborne sensor can only detect the obstacle information within the visual range L_s and visual angle θ_s, while the actual distance L and visual angle θ between UAV and obstacle can be calculated by

$$\begin{cases} L = \sqrt{(x_i^G - x_j^G)^2 + (y_i^G - y_j^G)^2} \\ \theta = \arctan \frac{y_i^G - y_j^G}{x_i^G - x_j^G} \end{cases} \tag{1}$$

where $P_i^G = [x_i^G, y_i^G, z_i^G]^T$ is the coordinate of UAV in geodetic coordinate system and $P_j^G = [x_j^G, y_j^G, z_j^G]^T$ is the coordinate of obstacle in geodetic coordinate system.

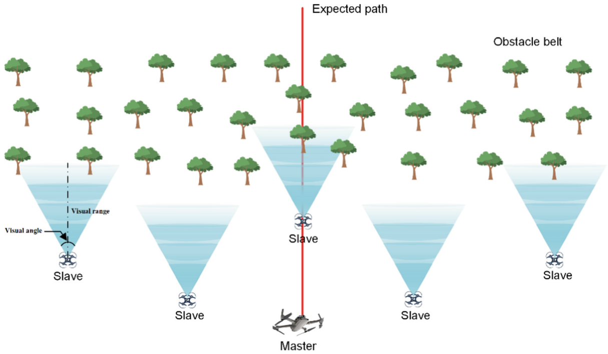

Fig. 1. Scenario assumption of multi-sensor information fusion

As illustrated in Fig. 1, at this moment, each UAV can obtain local and inaccurate information about the obstacle belt merely due to limited detection ability and sensor uncertainty. Therefore, it is necessary and essential to cooperate the whole information through information fusion to improvement the overall detection ability and achieve a global situation awareness.

3 Information Fusion Based on D-S Evidence Theory

3.1 Framework of D-S Evidence Theory

The D-S evidence theory mainly consists of three elements: discernment frame, basic probability assignment function and combination rule.

- Discernment frame (DF)

A set Θ composed of independent, complete, and exclusive elements $O_1, O_2, \cdots, O_n$ is called the discernment frame in D-S evidence theory. Its power set 2^Θ contains all possible subsets of the identification framework, which can be expressed as

$$2^\Theta = \{ \emptyset, \{ O_1 \}, \{ O_2 \}, \cdots, \{ O_n \}, \{ O_1 \cup O_2 \}, \{ O_1 \cup O_3 \}, \cdots, \Theta \} \quad (2)$$

where $\{\emptyset\}$ represents no obstacle is detected, $\{ O_1 \}$ represents the Obstacle I is detected, and $\{O_1 \cup O_2\}$ indicates either Obstacle I or Obstacle II is detected.

- Basic probability assignment (BPA) function

The BPA function is defined to better describe "uncertainty" and "unknown". Assume each obstacle O_i maps to a function $m(O_i)$ ($m(O_i) \in [0, 1]$). If m satisfies

$$m(\emptyset) = 0; m(O) \geq 0; \sum_{o \in 2^\Theta} m(O) = 1, \quad (3)$$

then, m could be qualified as a BPA function on Θ. $m(O)$ represents the support degree for evidence, excluding support for any true subset of O.

In our research, The BPA function is expressed by

$$m(O) = \frac{e^{-\frac{\theta_t^2}{2\lambda^2}}}{\sqrt{2\pi}\lambda}\sqrt{2\pi}\lambda e^{-L_t/\mu} = e^{-\frac{\theta_t^2}{2\lambda^2}\frac{L_t}{\mu}} \quad (4)$$

The visual angle θ_t and the visual distance L_t at time t can be expressed as

$$\begin{aligned} \theta_t &= \arctan \frac{L_0 \tan \theta_0}{L_0 - vt} \\ L_t &= L_0 - vt \end{aligned} \quad (5)$$

where θ_0 refers to the visual angle when UAV detects obstacles at initial time and L_0 is the visual distance at initial time.

It is not difficult to verify that the BPA function constructed in Eq. (4) meets the conditions in Eq. (3).

- Combination rule

The Dempster combination rule is adopted in our research. After determining the DF and BPA function, two sets of independent BPA function $m_1(O)$ and $m_2(O)$ is available to be fused through

$$\begin{aligned} m(O) &= (m_1 \oplus m_2)(O) = \frac{1}{k} \sum_{O_1 \cap O_2 = O} m_1(O_1)m_2(O_2) \\ K &= \sum_{O_1 \cap O_2 \neq \emptyset} m_1(O_1)m_2(O_2) = 1 - \sum_{O_1 \cap O_2 = \emptyset} m_1(O_1)m_2(O_2) \end{aligned} \quad (6)$$

where K is a conflict coefficient that represents the degree of conflict between different pieces of evidence. The combination rule of double evidence can be extended to multiple since the result of evidence fusion is not related to the fusion sequence.

The following is the detailed process of information fusion. Two aspects of information are supposed to be fused to improve the awareness accuracy.

3.2 Information Fusion Among Different UAVs

Assume several UAVs detect an obstacle at time t, the first step is to fuse information from all UAVs covering the obstacle at this moment. Figure 5 illustrates the step, where $m_1(O_1)$ represents the BPA function of Obstacle I detected by UAV I, $P_1^G(O_1)$ describes the coordinate of in geodetic system detected by UAV I (Fig. 2).

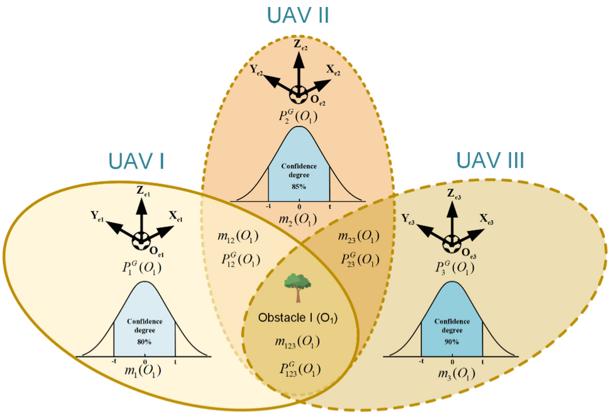

Fig. 2. Information fusion among different UAVs

Without loss of generality, the information fusion between UAV I and UAV II on Obstacle I is taken as an example. Normalized constant K is calculated by

$$\begin{aligned} K =& 1 - \sum_{O_1 \cap \cdots \cap O_n = \emptyset} m_1(O_1) \cdot m_2(O_2) \cdots m_n(O_n) \\ =& 1 - [m_1(O_1) \cdot m_2(O_2) + \cdots + m_1(O_1) \cdot m_n(O_n) \\ & + m_1(O_2) \cdot m_2(O_1) + \cdots + m_1(O_2) \cdot m_n(O_n) \\ & + \cdots + m_1(O_n) \cdot m_2(O_1) + \cdots + m_1(O_n) \cdot m_n(O_{n-1})] \end{aligned} \tag{7}$$

Subsequently, the BPA function and coordinate are fused by

$$\begin{cases} m_{12}(O_1) = m_1(O_1) \oplus m_2(O_1) = \dfrac{\sum\limits_{O_1 \cap O_1 = O_1} m_1(O_1) m_2(O_1)}{K} = \frac{1}{K} \cdot [m_1(O_1) \cdot m_2(O_1)] \\ P_{12}^G(O_1) = \frac{m_1(O_1) \cdot P_1^G(O_1) + m_2(O_1) \cdot P_2^G(O_1)}{m_1(O_1) + m_2(O_1)} \end{cases} \tag{8}$$

Through this step, the BPA function and coordinate information fusion results of UAV I and II for Obstacle I at time t are obtained. Then, fuse the results with the remaining UAVs in turn, and the overall information fusion results of Obstacle I at time t under the detection of all UAVs will be obtained.

3.3 Information Fusion Among Different Moments

In addition, the fusion results at time t are required to fuse with other information at different moments. The schematic diagram is shown in Fig. 3, where $m_{1\ldots N}^{t_1}(O_1)$ represents the BPA function of Obstacle I detected by the whole formation at moment t_1, $P_{1\ldots N}^{G,t_1}(O_1)$ describes the coordinate of in geodetic system detected by UAV I.

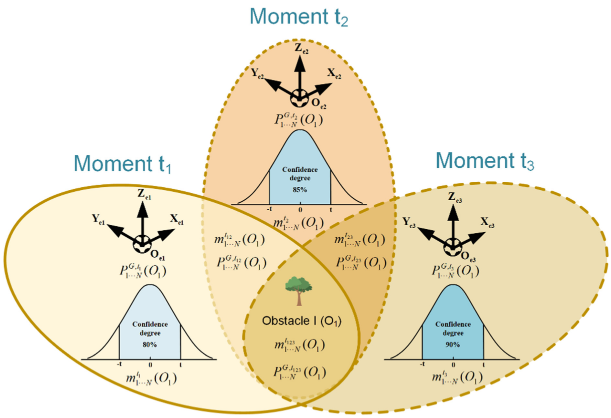

Fig. 3. Information fusion among different moments

Similarly, the information fusion between time t_1 and time t_2 on Obstacle I is taken as an example and the normalized constant k is calculated by

$$
\begin{aligned}
K &= 1 - \sum_{O_1 \cap \cdots \cap O_n \neq \emptyset} m_1(O_1) \cdot m_2(O_2) \cdots m_n(O_n) \\
&= 1 - [m_{1\ldots N}^{t_1}(O_1) \cdot m_{1\ldots N}^{t_2}(O_2) + \cdots + m_{1\ldots N}^{t_1}(O_1) \cdot m_{1\ldots N}^{t_2}(O_n) \\
&+ m_{1\ldots N}^{t_1}(O_2) \cdot m_{1\ldots N}^{t_2}(O_1) + \cdots + m_{1\ldots N}^{t_1}(O_2) \cdot m_{1\ldots N}^{t_2}(O_n) \\
&+ \cdots + m_{1\ldots N}^{t_1}(O_n) \cdot m_{1\ldots N}^{t_2}(O_1) + \cdots + m_{1\ldots N}^{t_1}(O_n) \cdot m_{1\ldots N}^{t_2}(O_{n-1})]
\end{aligned} \tag{9}
$$

Subsequently, the BPA function and coordinate are fused by

$$
\begin{cases}
m_{1\ldots N}^{t_{12}}(O_1) = m_{1\ldots N}^{t_1}(O_1) \oplus m_{1\ldots N}^{t_2}(O_1) = \dfrac{1}{K} \cdot [m_{1\ldots N}^{t_1}(O_1) \cdot m_{1\ldots N}^{t_2}(O_1)] \\
P_{1\ldots N}^{G,t_{12}}(O_1) = \dfrac{m_{1\ldots N}^{t_1}(O_1) \cdot P_{1\ldots N}^{G,t_1}(O_1) + m_{1\ldots N}^{t_2}(O_1) \cdot P_{1\ldots N}^{G,t_2}(O_1)}{m_{1\ldots N}^{t_1}(O_1) + m_{1\ldots N}^{t_2}(O_1)}
\end{cases} \tag{10}
$$

Through this step, the BPA function and coordinate information fusion results of all UAVs for Obstacle I at the later moment t_2 are obtained.

Finally, fuse the results with the subsequent moments in turn, and the overall information fusion results of Obstacle I under the detection of all UAVs at all times will be obtained, that is, the final result of cooperative situation awareness.

4 Case Study

In this section, the information fusion method is applied to the scenario illustrated in Fig. 1. The fusion results among several common formations are discussed. Besides, the simulation experiments are conducted with MATLAB2019Ra software on Windows 10 system, and the parameters of cooperative awareness are set as follows (Table 1).

Table 1. Simulation parameters of cooperative awareness

Item	Parameter	Item	Parameter
Obstacle space	300 * 200 * 100 m	Sampling cycle	1 s
n_{obs}	50	L_s	0–550 m
n_{uav}	5	θ_s	−45°–+45°

4.1 Cooperative Situation Awareness Under Fixed Formation

Firstly, we fuse the obstacle information detected by UAVs under a specific fixed formation. The distribution of UAV and obstacle is shown in Fig. 7 and (Fig. 4)

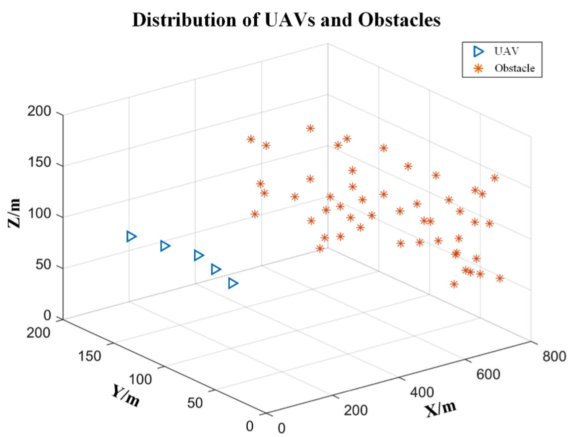

Fig. 4. Distribution of UAVs and obstacles under fixed formation

Subsequently, we project the results of information fusion onto the X-Y plane and obtain the fusion results of the first ten sampling times, as shown in Fig. 8, where the circle refers to the obstacle with confidence in interval [0, 0.2], the square represents the obstacle with confidence in interval (0.2, 0.4], the asterisk represents the obstacle with confidence in interval (0.4, 0.6], the right triangle represents the obstacle with confidence in interval (0.6, 0.8], and the cross represents the obstacle with confidence in interval (0.8, 1.0].

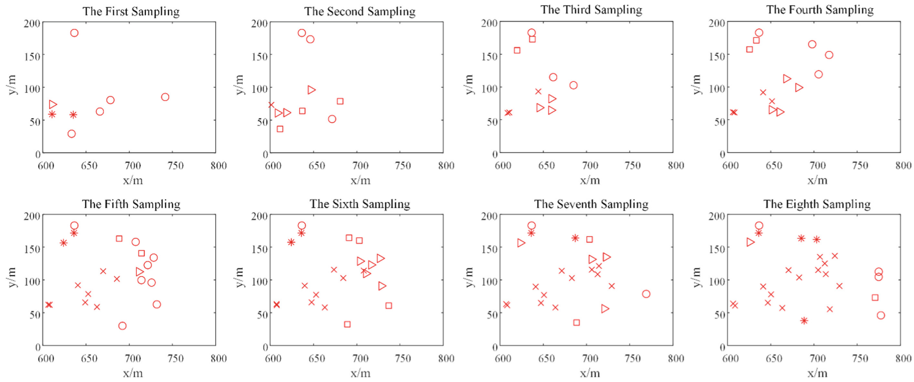

Fig. 5. Results of the first eight times

As illustrated in Fig. 5, the number of identified obstacles shows a considerable rise as the sampling cycle varies, while the confidence of the same obstacle also ascends. Combined with UAV formation and sensor ability, the following conclusions can be drawn for the same obstacle, as more pieces of information are fused, the uncertainty of fusion results decreases and the confidence increases. Besides, when sampling cycles are constant, the farther the obstacle is from the formation center, the lower the confidence of obstacle is. In addition, most of the obstacle points are marked with cross during the eighth sampling, which means a majority of obstacles have been detected by airborne sensors. This phenomenon also verifies the validity of the information fusion method.

4.2 Cooperative Situation Awareness Under Flexible Formation

Subsequently, we considered the influence of formation on fusion and applied five common formations into the proposed method. The different formations are illustrated as follows (Fig. 6).

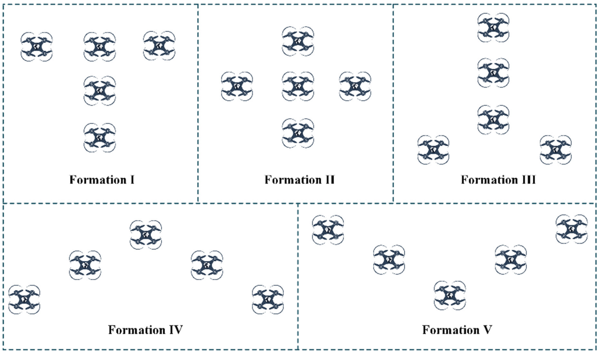

Fig. 6. Five common formation shapes

The simulation result is illustrated in Fig. 7.

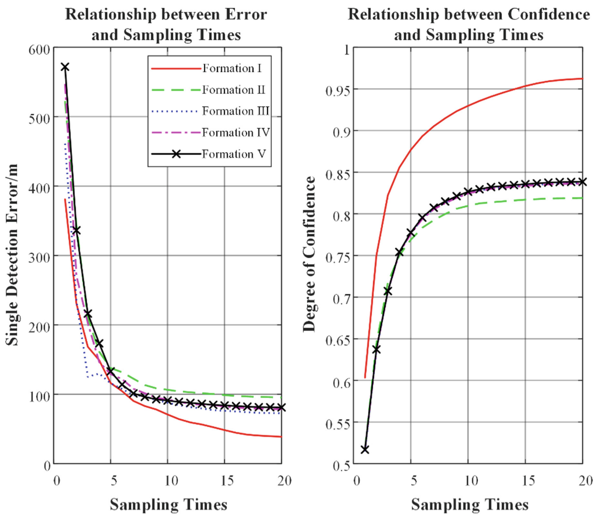

Fig. 7. Fusion result under flexible formations

The detection error and detection confidence of three regions under five common formations were compared. As can be seen from Fig. 7, with the increase of sampling times, the error of the fusion result decreases sharply before the fifth sampling and becomes steady afterwards, while and the confidence becomes higher and higher. Moreover, compared with other formations, Formation I indicates the smallest detection error and the highest confidence. The figures achieve 50 m and 96.58%, respectively. In conclusion, the sensor detection range can completely cover the obstacle area in the fifth sampling cycle. Subsequently, the error and confidence curve of the fusion result are stable in the whole sampling cycle.

5 Conclusion and Future Work

Based on the background of cooperative operation, this paper applies D-S evidence theory to multi-UAVs cooperative situation awareness to conduct the information fusion detected by airborne sensors, which indicates a superior performance dealing with sensor uncertainty caused by sensors' inherent characteristics and the errors in manufacturing and assembly. In the case study of cooperative situation awareness under fixed and flexible formations, the uncertainty of fusion results decreases, and the confidence increases as more pieces of information are fused. Via the numerical results, it was verified that D-S evidence theory is superior to multi-UAVs information in improving the detection accuracy and achieving a global situation awareness. The single detection error was analyzed, and the degree of confidence under different formations were also illustrated by a diagram of curves.

Future work will include the distribution modeling of dynamic obstacles, and the improvement of information fusion method will also be considered.

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