Cause Analysis of Consumer-Grade UAV Accidents Based on Grounded Theory-Bayesian Network

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Abstract: In order to reduce the accident rate of consumer-grade unmanned aerial vehicles (UAVs) in daily use scenarios, the accident causes are analyzed based on the accident cases of consumer-grade UAVs. By extracting accident causing factors based on the Grounded theory, the relationship between these factors is analyzed. The Bayesian network for consumer-grade UAV accidents is constructed. With the Grounded theory-Bayesian network, the probability of four types of accidents is inferred: fall, air collision, disappearance, and personal injury. With the posterior probability of each factor being reversely reasoned, the causal chain with the maximum probability of each accident is obtained. After the sensitivity of each factor is analyzed, the key nodes in the network accordingly are inferred. Then the causing factors of consumer-grade UAV accidents are analyzed. The results show that the probability of fall accident is the highest, the fall accident is associated with the probabilistic maximum causal chain of personal injury, and the sensitivity analysis results of each type of accident as the result node are inconsistent.

Key words: consumer-grade UAV; Grounded theory; Bayesian network; key nodes; accident causes

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0 Introduction

With the continuous advancement of technology, the performance of unmanned aerial vehicles (UAVs) has been significantly improved, but flight accidents of consumer-grade UAVs with low entry barriers and the largest holdings still exist. Most of the existing consumer-grade UAV operators have not received systematic skill training and safety education, resulting in a high risk of UAV operation. In addition, these UAVs are prone to accidents, which brings high risks to air transportation. The production standards of UAV manufacturers are not uniform and the quality is not up to standard, which also lays a hidden danger for the safe use of consumer-grade UAVs. Therefore, it is necessary to analyze the causes of consumer-grade UAV accidents to improve the operation safety level.

In UAV collision risk field, many new UAV collision models through mathematical analysis have proposed, which have achieved relative success[1-3]. The fall risk of logistics UAVs is used to analyze the main reasons for the failure of UAVs[4]. Based on the system theoretic accident model and process (STAMP), a safety control model is built for UAV low-altitude conflict resolution, and systems-theoretic process analysis (STPA) is used to identify and analyze key causes of unsafe behavior in the relief process[5]. By fully considering various environmental factors, new evaluation models are established for identifying UAV operation risk, which has achieved good results in application[6-8]. Based on the deep learning technology, a new model is built to solve the collision problem of drones with non-stationary objects during operation[9].

Operational risk is a hotspot in the field of UAVs, and some positive research results are obtained. Markov chains and equivalent safety level

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principles are used to model and validate accident-based UAV safety analysis[10]. Based on the analysis of the UAV accidents, the direct and indirect causes of the accidents are identified, and then the method is applied to the accident scene of a UAV target crash, which proves the effectiveness of this method[11]. Developed on the fault tree analysis model, the main hazards are determined for a UAV crash accident by analyzing the minimum cut set and structural importance of the model[12].

The key limitations of the above mentioned studies are: (1) These studies mainly focus on the UAV collision model and UAV safety risk assessment, while few studies pay attention to the causation analysis of UAV accidents; (2) many studies fail to notice the huge difference in safety levels between consumer-grade UAVs and industrial UAVs; (3) some studies just consider a certain accident, and the conclusions provided by them are not persuasive enough to analyze the causation theory of UAV accidents adequately[10]. To address these problems, the method of Grounded theory-Bayesian network for UAV accidents cause analysis is put forward with the following contributions: (1) 208 cases of consumer-grade UAV accidents are analyzed by the Grounded theory, and the rich accident cases make the extraction of accident causing factors more accurate; (2) a Bayesian network for consumer-grade UAV accidents is constructed, which fully considers the relationship between causal factors and the occurrence mechanism of each accident; (3) the maximum causal chain of various accidents is inferred by the Bayesian network, so the key factors of various accidents are obtained, which provides a reference for improving the safety level of consumer-grade UAV operation in the future.

The research objects of this paper are consumer-grade UAVs such as aerial photography. Compared with industrial UAVs, consumer-grade UAVs have more quantity and lower security, are more difficult to operate, supervise and certify pilots' qualifications, and operate in a more complex environment with a much higher accident rate than industrial UAVs. Therefore, in order to reduce UAV accidents and promote the development of the industry, it is necessary to conduct further research and analysis on the causing factors of consumer-grade UAV accidents.

1 Accident Cause Identification

Accident cases are collected through interviews and questionnaire surveys. There are 32 interviews and 176 questionnaires, a total of 208 cases. The accidents are caused by consumer-grade UAVs engaged in aerial photography activities.

The Grounded theory is a qualitative research method. It emphasizes the development of theoretical ideas based on data, suitable for research fields lacking theoretical explanations or insufficient existing explanations. The core of Grounded theory is the process of data collection and analysis, which mainly analyzes data through three steps: Open coding, axial coding, and selective coding[13].

1.1 Open coding

Open coding refers to coding the original data so that it presents the original attributes. Correctly reflecting the data content according to the concept and category, combining the same or similar types to extract the concept category. The initial appeared concepts are selected and categorized to gain 45 causing factor concepts and four accident concepts. With the acquired initial concepts being further integrated, 33 initial categories of causing factors and four initial categories of accident categories are obtained.

1.2 Axial coding

Axial coding is a deepening of open coding, which is continuously merged and clustered to establish relationships and express the association between various parts of the data. The categories obtained by open coding are further summarized and classified to form 13 independent categories of causing factors and two categories of accidents.

1.3 Selective coding

Selective coding is used to select the core category, process the relationship between the main categories, then analyze the relationship between the main categories. The essence of selective coding is to analyze the concept category system and select a core category. On the basis of the above-mentioned open coding and axial coding analysis, generalization, extraction, reorganization, and integration are carried out. Finally, three core categories of causing factors and one core category of accidents are summarized.

The extraction process of category development and coding implementation for the three types of codes is shown in Table 1.

Table 1 Process of category development and coding implementation

Concept	Initial category	Main category	Core category
(1) Not checked before takeoff (2) Insufficient inspection	(1) Missing check L_1	(1) Maintenance personnel factors	(1) Operators
(3) Hanging excessive weight (4) Unstable center of gravity caused by hanging heavy objects	(2) Incorrect load L_2		
(5) Operation error	(3) Operation error L_3	(2) UAV driver factors	
(6) Insufficient driver experience (7) Insufficient driver skills	(4) Lack of experience and skills L_4		
(8) Insufficient driver safety awareness	(5) Lack of safety awareness L_5		
(9) UAV motor failure (10) UAV electronic governor failure	(6) Motor fault H_1	(3) Powertrain failure	(2) UAV system
(11) Incorrect propeller installation (12) Propeller damage (13) Propeller fall off	(7) Propeller failure H_2		
(14) Single shaft lose power (15) Multi shaft lose power	(8) Lose power H_3		
(16) UAV battery failure	(9) Battery failure H_4	(4) Electrical system failure	
(17) UAV low battery	(10) Low battery H_5		
(18) Distance between UAV and ground control equipment is beyond the effective range	(11) Out of communication range H_6	(5) Communication system failure	
(19) Link between UAV and ground control equipment is lost	(12) Loss of communication link H_7		
(20) Ground control equipment failure	(13) Ground control equipment failure H_8	(6) Ground control equipment failure	
(21) Low battery of ground control equipment	(14) Low power of ground control equipment H_9		
(22) UAV loses normal flight attitude	(15) Attitude loss H_{10}	(7) Attitude loss	
(23) UAV flight controller failure	(16) Flight control fault H_{11}	(8) Flight control system fault	
(24) UAV compass fault	(17) Compass fault H_{12}		
(25) UAV satellite positioning system failure	(18) Satellite positioning system failure H_{13}		
(26) UAV compass disturbed	(19) Compass operation failure H_{14}	(9) Flight control system operation failure	
(27) UAV satellite signal loss	(20) Satellite signal loss H_{15}		
(28) UAV vision module is abnormal	(21) Vision module failure H_{16}		
(29) UAV flight direction error	(22) Flight direction error H_{17}	(10) Ground control failure	
(30) UAV lost control in the air	(23) Lose control H_{18}		
(31) UAV automatic flight	(24) Automatic flight mode H_{19}	(11) Autonomous flight mode	
(32) Dense fog	(25) Dense fog E_1	(12) Meteorological environmental factors	(3) Flight environment
(33) Low temperature	(26) Low temperature E_2		
(34) Heavy rain	(27) Heavy rain E_3		
(35) High wind	(28) High wind E_4		
(36) Magnetic field interference in the flight area	(29) Magnetic interference E_5	(13) Geographical environmental factors	
(37) Cloudy flight (38) Night flying (39) Dark light environment flight	(30) Weak light environment E_6		

Continued

Concept	Initial category	Main category	Core category
(40) Wire	(31) Low altitude obstacle E_7		
(41) Skyscrapers			
(42) Tree			
(43) Other obstacles			
(44) Bird strike	(32) Bird strike E_8		
(45) The flight area is densely populated	(33) Densely populated area E_9		
(1) UAV lost	(1) Disappearance	(1) UAV damage	(4) Accident type
(2) UAV air collision	(2) Air collision		
(3) UAV fall	(3) Fall		
(4) UAV fall and cause injury	(4) Personal injury	(2) Personal injury	

2 Accident Cause Modeling

2.1 Principle of Bayesian network

Bayesian network is the product of the combination of probability theory and graph theory. It is an uncertain causal correlation model[14], a two-tuple $B=(G, \theta)$ represents the Bayesian network, where $G=(V, E)$ represents the directed acyclic graph, V is the node set in the graph, and E the directed edge connecting two nodes in the graph, representing qualitative information; and θ represents the probability distribution between variables, i. e. conditional probability table, representing quantitative information. Under the given premise, the Bayesian network can update the probability of variables through probability propagation or reasoning under incomplete and uncertain conditions.

Assuming that the variable set in the Bayesian network is $V=\{X_1, \cdots, X_n\}$, according to the conditional independence assumption and chain rule in the Bayesian network structure, the joint probability distribution $P(V)$ of Bayesian network nodes can be expressed as

$$P(V)=\prod^{n} P(X_i/P_{\mathrm{a}}(X_i)) \tag{1}$$

where $P_{\mathrm{a}}(X_i)$ is the parent node set of X_i.

When the new premise $E=e$ is given, the posterior probability of variable V can be inferred through the Bayesian network, which is defined as

$$P(V/E=e)=\frac{P(V,E=e)}{P(E=e)} \tag{2}$$

where $E=e$ indicates that the value of variable E is e.

The node sensitivity analysis in the Bayesian network can find out the nodes that have an important influence on the result nodes. The formula is as follows

$$M=Y-X \tag{3}$$

where M represents the sensitivity of a node, Y the posteriori probability of a node, and X the priori probability of a node.

2.2 Construction of Bayesian network

Based on the consumer-grade UAV accident cases, by analyzing and sorting out the causal chain of the accident, the causal factors and the final accident are connected through a directed acyclic graph, then a Bayesian network graph is constructed. The steps are as follows:

(1) Determine the basic events in the network and take them as the root node.

(2) The relationship between nodes is determined according to the causal chain in the accident case, which is regarded as a directed arc in the network.

(3) Determine prior probability and conditional probability.

Four types of accidents and 33 causing factors are obtained from the cases. The four types of accidents are fall, air collision, disappearance, and personal injury, including 109 cases of fall, 47 cases of air collision, 36 cases of disappearance, and 16 cases of personal injury. Among the 33 cause factors, 18 factors are used as root nodes and 15 factors as intermediate nodes. The prior probability of the root node is obtained through accident cases. For example, there are 100 cases of low altitude obstacles in 208 accident cases, so the prior probability of low altitude obstacles is 48%. The prior probability of the root node is shown in Table 2.

Table 2 Prior probability of root node

Root node	Priori probability/%	Root node	Priori probability/%
Lack of experience and skills	17	Flight control fault	2.5
Operation error	7.5	Low altitude obstacle	48
Missing check	12	Magnetic interference	6
Lack of safety awareness	16	Dense fog	3.5
Ground control equipment failure	1	Weak light	5.5
Compass fault	2.5	High wind	11
Automatic flight mode	10.5	Low temperature	2.5
Satellite positioning system failure	1	Bird strike	1.5
Motor fault	1.5	Heavy rain	2

The conditional probability of the intermediate node is inferred from the causal relationship between the nodes in the accident case and further improved based on expert experience. For example, the probability of satellite signal loss is 100% in all accident cases with simultaneous satellite positioning system failure and low altitude obstacles, 100% in the accident cases with only satellite positioning system failure and no low altitude obstacles, and 23% in the case with only low altitude obstacles and no satellite positioning system failure, but the probability with no satellite positioning system failure and low altitude obstacles is 0%. However, because of the small number of accident cases, there may be incomplete coverage of accident causes. In comprehensive consideration, the probability of 0% here is too absolute, so expert experience correction is introduced to set the probability of occurrence to 0.1%. To sum up, the conditional probability of the satellite signal loss node is shown in Table 3(T indicates occurrence and F otherwise).

Table 3 Conditional probability of satellite signal loss node

Satellite positioning system failure	Low altitude obstacle	T/%	F/%
T	T	100	0
T	F	100	0
F	T	23	77
F	F	0.1	99.9

3 Accident Cause Analysis

The causing factors are the nodes in the network, the active relationship between the causal factors is the edge, reasoning down in turn, and the factors are connected to form the Bayesian network diagram of consumer-grade UAV accidents.

In the constructed Bayesian network, accidents are divided into four situations: Disappearance, air collision, fall, and personal injury. Air collision accidents may further deteriorate into fall accidents, and fall accidents may produce secondary accidents and personal injury under the condition of dense personnel. Therefore, it is necessary to analyze the relationship between causal factors and the occurrence mechanism of each accident in order to reduce the occurrence of accidents. The Bayesian network diagram is shown in Fig.1, which is simulated by the Netica software.

3.1 Forward reasoning and analysis

By inputting the prior probability or conditional probability of the node into the Bayesian network, the probability of final fall accident can be inferred to be 15%, the probability of air collision accident is 8.6%, the probability of disappearance accident is 4.85%, and the probability of personal injury accident is 1.71%. As shown in Fig.1, the probability of fall accident is the highest, followed by air collision, then disappearance and personal injury, which is consistent with the statistical results of accident cases used in this paper, indicating that the constructed Bayesian network is effective.

The highest probability of basic events is the existence of low-altitude obstacles. The main reasons are that the flight airspace of consumer-grade

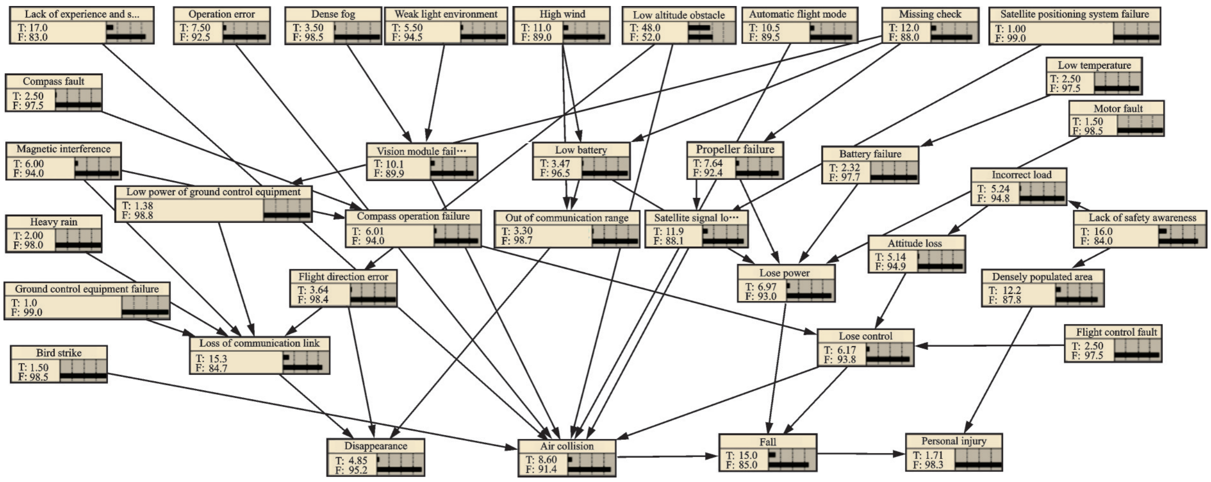

Fig.1　Bayesian network diagram of consumer-grade UAV accidents (unit: %)

UAVs is mostly ultra-low altitude or low altitude. There are many obstacles, such as buildings, trees, and wires, and the flight environment is complex. Secondly, the probabilities of lack of experience and skills and lack of safety awareness are also high. The main reasons are that the acquisition cost and operation threshold of consumer-grade UAVs are low, leading many operators have not received systematic skills and safety education, which are consistent with the current situation. Through the Bayesian network, the accident probability of the combination of the factors causes the operators, UAV system and flight environment can be deduced forward. Taking the low altitude obstacle with the highest priori probability in the root node as an example, this paper researches the occurrence probability of various accidents when there are different combinations of operator and flight environment factors in the root node in the presence of low altitude obstacles. The results are shown in Fig.2.

Fig.2 shows that when low altitude obstacles (E_7), lack of experience and skills (L_4), and automatic flight mode (H_{19}) occur at the same time, the most likely accident is air collision, with a probability of 61%. When low altitude obstacles (E_7), lack of experience and skills (L_4), and motor fault (H_1) occur at the same time, the most likely accident is fall, with a probability of 72.2%. The comparative analysis shows that the automatic flight model (H_{19}) has a greater influence on air collision, and motor fault (H_1) has a greater influence on falls. By analogy, the probability of various accidents is analyzed when different causing factors interact, and those accidents are more affected by various causal factors.

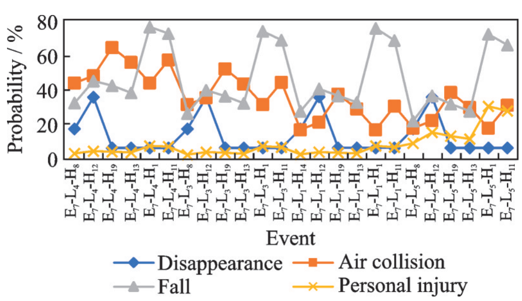

Fig.2　Occurrence probability of various accidents with low altitude obstacles

3.2　Reverse reasoning and analysis

The posterior probability reverse reasoning function of the Bayesian network is used to analyze the generation process of consumer-grade UAV accidents. The probability of disappearance, air collision, fall, and personal injury is set to 100%, and then the posterior probability distribution of each node in four cases is obtained, as shown in Fig.3.

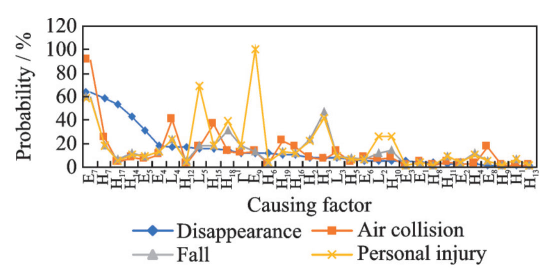

Fig.3　Posterior probability of each node

When there is a disappearance accident, the most likely cause chain is shown in Fig.3. Another important reason for the loss of the communication link (H_7) is the presence of magnetic interference (E_5), with a probability of 31%. In addition, the flight direction error (H_{17}) of UAV is also the main cause of the disappearance, with a probability of 53.2%, and the flight direction error (H_{17}) is usually caused by compass operation failure (H_{14}), with a probability of 43.1%, of which the probability of compass operation failure (H_{14}) caused by magnetic interference (E_5) is the highest.

When an air collision accident occurs, the maximum accident probability is shown in Table 3. The second is the collision caused by the satellite signal loss (H_{15}). The cause of the collision is the satellite signal loss (H_{15}) and the presence of low-altitude obstacles (E_7). The probability of satellite signal loss (H_{15}) is 36.7%. The presence of low altitude obstacles (E_7) is also the main cause of satellite signal loss (H_{15}).

When a fall accident occurs, the chain of causes with the largest accident probability is shown in Table 3. Battery failure (H_4) and low battery (H_5) are also important reasons for losing power (H_3), with the probability of 11.3% and 7.59%, respectively. Because a part of collision accidents will further deteriorate into fall accidents, when the fall occurs, the probability of air collision is 35.4%. In addition, lose control (H_{18}) is also an important cause of the fall.

As the personal injury is the follow-up accident of UAV fall, they will only occur when the fall and the densely populated area (E_9) occur at the same time. At this time, the probabilistic maximum causal chain of accidents is shown in Table 4. Unlike fall accident, the probability of fall caused by lose power (H_3) and air collision is reduced, and the probability of fall caused by lose control (H_{18}) increases. This is because of lack of safety awareness (L_5). At the same time, it may also cause incorrect load (L_2), which may cause attitude loss (H_{10}) and cause an uncontrolled fall.

Table 4 Probabilistic maximum causal chain of accidents

Accident category	Probabilistic maximum causal chain
Disappearance	Low altitude obstacle→Loss of communication link→Disappearance
Air collision	Lack of experience and skills and there are low altitude obstacles→Air collision
Fall	Missing check→Propeller failure→Lose power→Fall
Personal injury	Lack of safety awareness→Densely populated area and fall→Personal injury

3.3 Sensitivity analysis

Bayesian network sensitivity analysis can be used to measure the influence of cause nodes on result nodes. Different accidents are selected as result nodes respectively. And Netica software is used to analyze the sensitivity of causing factors for consumer-grade UAV accidents. The results are shown in Fig.4.

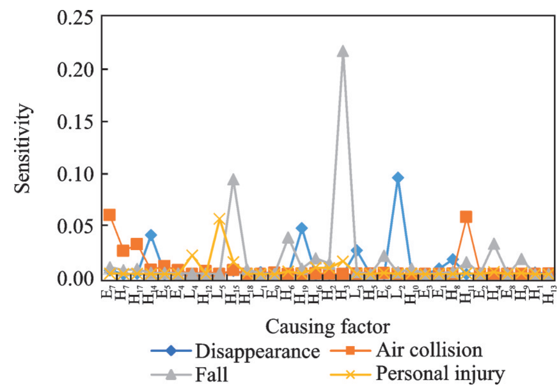

Fig.4 Sensitivity analysis of causing factors

When disappearance, air collision, fall, and personal injury accidents are selected as the target nodes, the causing factors with significantly higher sensitivity in the network are selected, as shown in Table 5. Because fall is the precondition of personal injury, the lose power (H_3) and lose control (H_{18}) with high sensitivity in fall accidents are also highly sensitive in personal injury accidents.

Table 5 Cause factors with significantly higher sensitivity

Accident category	Sensitivity
Disappearance	Flight direction error; Compass operation failure; Loss of communication link; Magnetic interference; Compass fault
Air collision	Bird strike; Low altitude obstacle; Loss of satellite signal; Lack of experience and skills
Fall	Lose power; Lose control; Propeller failure; Battery fault
Personal injury	Densely populated area; Lack of safety awareness; Lose power; Lose control

For fall accidents and personal injury accidents, the sensitivity of lose power (H_3) and lose control (H_{18}) is high, so there are 15 high sensitivity nodes in the four types of accidents in the network.

Nodes with high sensitivity have a great influence on the Bayesian accident network which are the weak link of the system. When the probability of these node changes, the probability of accident nodes will also change greatly. Therefore, they can be regarded as key nodes in the network and need to be focused on prevention and control.

4 Conclusions

Based on the consumer-grade UAV accident cases, the accidents causing factors are extracted by the Grounded theory, then the Bayesian network is constructed to analyze the relationship between the causal factors and the accident probability according to the accident causal chain.

(1) Based on the accident cases, the causes of consumer-grade UAV accidents are summarized and analyzed by the Grounded theory, which consists of 33 initial categories, 13 main categories, and three core categories.

(2) Among the four types of accidents, fall has the highest probability, with a probability of 15%, and the probabilistic maximum causal chain of personal injury is similar to that of fall accidents.

(3) There are 15 key nodes in the consumer-grade UAV accident cause network. Among them, the factor that has the greatest influence on the disappearance accident is flighted direction error, the greatest influence on the air collision is bird strike, the greatest influence on the fall is lose power, and the greatest influence on personnel injury is a densely populated area.

The accident causes of consumer-grade UAVs are studied, while relevant research on the accident causes of other types of UAVs such as industrial UAVs, unmanned helicopters, and fixed-wing UAV needs further consideration.

References

[1] WAGGONER B. Developing a risk assessment tool for unmanned aircraft system operations[D]. Seattle: University of Washington, 2010.

[2] BAI H, HSU D, KOCHENDERFER M J, et al. Unmanned aircraft collision avoidance using continuous-state POMDPs[C]//Proceedings of Conference on Robotics: Science and Systems Ⅶ. Los Angeles, CA, USA: [s.n.], 2011.

[3] YANG M. Safety risk assessment of collision between UAV and civil airliner [D]. Guanghan: Civil Aviation Flight University of China, 2019. (in Chinese)

[4] HAN P, WANG M Q, ZHAO Y F. Failure risk assessment of logistics UAV based on Bayesian network[J]. Journal of Safety Science and Technology, 2020, 16(11): 178-183. (in Chinese)

[5] ZHANG H H, GAN X S, SUN J J, et al. Analysis of low altitude UAV conflict resolution safety based on STPA-TOPAZ[EB/OL]. (2021-08-02). Acta Aeronautica et Astronautica Sinica. http://kns.cnki.net/kcms/detail/11.1929. V. 20210619.0051.012. html. (in Chinese)

[6] PRIMATESTA S, RIZZO A, LA C H A. Ground risk map for unmanned aircraft in urban environments[J]. Journal of Intelligence & Robitic Systems, 2020, 97: 489-509.

[7] HU X T, DAI F Q. Risk assessment model for UAV operation considering safety of ground pedestrians in urban areas[J]. China Safety Science Journal, 2020, 30(8): 137-142. (in Chinese)

[8] BU J, ZHANG H H, HU M H, et al. Risk assessment of unmanned aerial vehicle flight based on K-means clustering algorithm[J]. Transactions of Nanjing University of Aeronautics and Astronautics, 2020, 37(2): 263-273.

[9] MORA A. Collision avoidance on unmanned aerial vehicles using neural network pipelines and flow clustering techniques[J]. Remote Sensing, 2021, DOI: Http://doi.org/110.3390/rs13132643.

[10] FAN F. Research on flight safety analysis method of UAV based on accident[D]. Nanjing: Nanjing University of Aeronautics and Astronautics, 2019. (in Chinese)

[11] WU Z G, LUO Q F, HUANG Z J, et al. Unmanned aerial vehicle accident analysis based on integrated graphical modeling and HFACS[J]. Electronic Product Reliability and Environmental Testing, 2020, 38(4): 84-87. (in Chinese)

[12] LIANG P, GUO H L, QIAN J R, et al. Risk analysis and countermeasures research of UAV crash accident based on FTA model[J]. Management & Tech-

nology of SME, 2020, 38(4): 84-87. (in Chinese)

[13] YUE R T, LI J W, HAN M. Cause analysis of aviation accidents based on complex network theory[J]. Transactions of Nanjing University of Aeronautics and Astronautics, 2021, 38(4): 646-655.

[14] ZHU J C, ZHU X G, GUAN L. On the emergency evacuation of the personnel in the chemical enterprises based on the Bayesian network[J]. Journal of Safety and Environment, 2021, 21(2): 739-745. (in Chinese)

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Author contributions Dr. **YUE Rentian** designed the research, compiled the model, explained the model results, analyzed the results, and wrote the manuscript. Mr. **HAN Meng** provides data and Bayesian network model components. Mr. **HOU Bowen** participated in data analysis and manuscript writing. All authors commented on the manuscript draft and approved the submission.

Competing interests The authors declare no competing interests.

(Production Editor: ZHANG Huangqun)

基于扎根理论-贝叶斯网络的消费级无人机事故致因分析

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摘要：为了降低日常使用场景中消费级无人机(Unmanned aerial vehicles, UAVs)的事故率，根据消费级无人机事故案例分析了事故致因。通过扎根理论提取事故致因因素，分析了这些因素之间的关系。构建了消费级无人机事故的贝叶斯网络。利用扎根理论-贝叶斯网络，推断出坠落、空中碰撞、失踪和人身伤害4种类型事故的概率。通过对各因素的后验概率进行反向推理，得到了各事故概率最大的因果链。在分析每个因素的敏感性之后，相应地推断出网络中的关键节点。然后分析了消费级无人机事故的致因因素。结果表明，坠落事故概率最高，坠落事故与人身伤害概率最大因果链相关，作为结果节点的各类事故的敏感性分析结果不一致。

关键词：消费级无人机；扎根理论；贝叶斯网络；关键节点；事故致因