Research Article

A Design of a Developable Automatic Avoidance System of UAV Based on ADS-B

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There are two primary defects in the existing UAV avoidance systems: the system is memoryless; airborne radars are used to detect long-distance barriers, which are unreliable and expensive. The paper adopts the deep learning algorithm and ADS-B communication system based on a satellite base station to solve the above problems. It divides the avoidance problem into two parts: short-distance obstacle avoidance and long-distance route planning. On the one hand, the system establishes the knowledge base storing the previous avoidance experience and the matching mechanism, realizing the correspondence between input and experience through a deep learning algorithm. They can dramatically improve the reaction speed and safety of UAVs. On the other hand, the system realizes the interconnection between UAV and the satellite base station through the ADS-B communication system to replace the radars, putting the task of route planning on the satellite platform. Therefore, the satellite can achieve large-scale and all-weather detection to improve the overall safety of UAVs depending on its high and long-range characteristics. The paper also illustrates the design elements of the RF baseband integrated ADS-B transceiver and the simulation performance of the short-distance avoidance system in the end, whose results show that the system can be applied to dense obstacle environments and significantly improve the security of UAVs in a complex domain.

1. Introduction

The research on UAV avoidance systems is becoming increasingly mature, but there are two significant matters. The first problem is that the reacting speed of the current algorithm used in UAV is slow. The second question is that airborne radars primarily are used to collect environmental information in a far range, which are expensive and easily affected by the environment. This paper proposes a developable automatic avoidance system of UAV with fast response speed, referred to as DAS in the following.

On the one hand, the DAS can connect the UAV and satellite platform through the ADS-B receiver, so that the satellite can plan the safe route according to the information sent by ADS-B OUT and the environment information of UAV. Therefore, the UAV only needs to be equipped with infrared, ultrasonic, and other basic sensors, omitting the airborne radar to save the cost. At the same time, the performance requirement of CPU is further reduced due to the route planning put on the satellite platform.

On the other hand, there is a special subsystem in the DAS to avoid the close obstacles. The subsystem establishes a fast response mechanism for obstacle to avoidance method imitating the reflection system of human. The human reflex system enables us to dodge quickly when encountering obstacles. For example, if we face the vehicle, we will run to the side subconsciously, and the whole process is often not involved in the cerebral cortex. The key of the mechanism of UAV is to build knowledge bases to store the training experience, including the obstacle base that stores the type of obstacle, the strategy base that stores the corresponding solutions, and the mapping relationship between them. In short, the DAS gets the surrounding information according to the sensing data at first, which is used as the input of the subsystem. Then, the input is classified according to its characteristic information. If it can be divided into existing obstacle patterns, the system will directly determine the avoidance scheme according to the mapping relationship, without going through the underlying calculation and search. Therefore, the response time of the system will be greatly reduced

after full training, which can provide a strong guarantee for the emergency avoidance of UAVs.

2. Related Work

Traditional avoidance algorithms, such as A* [1, 2] and Voronoi diagram [3, 4], need to know the environment information in advance, so they are difficult to be used in the dense obstacle environment. Vanek et al. proposed a model predictive control algorithm [5] to solve the avoidance problem in the dense dynamic obstacle environment in finite time. Khattib uses a real-time fluid method to design an obstacle avoidance method [6] for multiple irregular obstacles. When UAV faces sudden obstruction, it often needs a lot of calculation to determine the avoidance mode, which requires a large amount of analysis and will cause a tremendous waste of resources.

The trend that deep learning technology is applied to the field of intelligent devices is increasing with the development of artificial intelligence. For example, Simmons constructs an autonomous walking robot [7] based on behavior decision control by using the Brooks behavior hypothesis criterion [8], which can plan and record avoidance paths. Therefore, the robot can continue to learn strange environments. Sandini et al. have constructed cognitive development robots [9] following the way of human thinking. Although the advanced intelligent algorithm solves the memoryless problem of traditional algorithms, these developmental mechanisms often need to be extracted, so it is difficult to deal with sudden obstacles. In addition, they may cause the data disaster through long-time development.

The ADS-B system based on satellite is gradually mature, such as the ALAS system, which can achieve strong monitoring in a wide range. Zhen proposed a low-risk fast avoidance mechanism [10] according to the field potential theory and ADS-B technology. However, most researchers' application is limited in ADS-B IN wasting a lot of computing resources and wide range monitoring characteristics of the satellite platform.

3. Overall System Design

According to the distance between the UAV and the block, the system is split into two parts: the short-distance avoidance subsystem (referred to as the SAS) and the long-distance avoidance subsystem (referred to as the LAS).

The LAS uses an ADS-B transceiver integrated with the RF baseband to establish the link between UAV and the satellite base station, where the route planning algorithm and long-distance obstacle detection are carried out. Therefore, the UAV only needs to broadcast its information and receive control signals coming from the satellite.

The knee jump reflex is the most straightforward reflex system in the human body, whose sensory neurons are directly related to motor neurons. After sensory neurons feel stimulated, they transmit control signals to motor neurons directly, without passing through the cerebral cortex.

The SAS mimics the knee jump reflection of the human body and builds three kinds of bases according to deep learn-

ing. The case base is to store obstacle samples, the strategy base is to store avoidance schemes, and the mapping base is to store the one-to-one correspondence between cases. When the sensors detect the perils, the system first tries to match the barrier with the samples in the case base in line with a specific algorithm. If it works, the corresponding avoidance scheme can be directly called according to the mapping relationship. The safety route can be determined without using the underlying algorithm. Thus, the SAS can significantly improve the security of UAVs in dense obstacle environments. Its principle is shown in Figure 1.

4. System Implementation Principle

4.1. Design of the SAS. The SAS includes the prediction module, the matching module, the development module, the bottom module, the validity detection module, and the knowledge base. The specific avoidance process can be divided into the following six steps, as shown in Figure 2.

Step 1. Collision Prediction. According to the output of the sensor system, the three-dimensional dynamic model of the obstacle and the machine is established in the obstacle prediction module, and the dangerous spherical area is set with the obstacle as the ball center. When the direction of the velocity vector of the UAV relative to the barrier intersects with the danger zone, it is considered that there is a possibility of collision. It enters step 2; otherwise, repeat step 1.

Step 2. Obstacle Matching. Match the input with the samples in the case base. If it does, enter step 3; otherwise, enter step 4.

Step 3. Scheme Reference. The SAS directly uses the existing avoidance strategies in its knowledge base and then enter step 5.

Step 4. Scheme Operation. Calculate the avoidance strategy according to the bottom obstacle avoidance algorithm, and enter step 5.

Step 5. Validity Judgment. After adjustment, the SAS predicts again. If the relative velocity direction of the UAV no longer intersects with the danger zone, the project is practical; enter step 6. Otherwise, it indicates that there is still a possibility of collision; return to step 4.

Step 6. Supplement Database. If the system has not entered step 4, return to step 1 directly. Otherwise, the information and avoidance strategy of the obstacles will be introduced into the self-development module, where the knowledge base will be supplemented before returning to step 1.

4.2. Design of the LAS. In the LAS, as shown in Figure 3, the UAV transmits the radio frequency signal containing its information through broadcast firstly. Then, the satellite platform plans the safe route and returns the control signal according to the position and speed of the UAV and the surrounding environment. UAV only needs to analyze and execute the control signal to realize the long-distance route planning of UAVs.

At the same time, point-to-point communication can be realized between different UAVs through ADS-B. The LAS can recognize the coordinated operation of the aircraft group

FIGURE 1: UAV anticollision system. It describes the architecture of the whole system.

FIGURE 2: The SAS process. It explains the workflow of the SAS.

through ADS-B, which significantly improves the security of cooperative defense action of crewless aerial vehicles.

5. Main Algorithms of the SAS

The SAS needs the following three algorithms to make it directly use the existing experience when avoiding close obstacles.

- (1) Matching algorithm. It is used to find samples similar to this obstacle
- (2) Underlying algorithm. It is used to determine the fundamental obstacle avoidance strategy
- (3) Self-development algorithm. It is used to supplement the knowledge base and establish the mapping relationship

FIGURE 3: The principle of LAS. It shows the application of ADS-B in the LAS.

FIGURE 4: Structure of the SOFM network.

5.1. Obstacle Matching Algorithm. This paper uses the SOFM network to realize the fuzzy matching between input obstacles and samples, which includes the output layer (competition layer) and input layer, as shown in Figure 4.

The training process of the SOFM network is shown in Figure 5. Each input sample of the SOFM network corresponds to a neuron in the input layer. The relationship between the input neuron and the output neuron is established by the weight vector. In this paper, the output layer adopts a two-dimensional chessboard topology, and each output neuron is connected to the surrounding neurons. When the eigenvector of a sample is input into the network, a neuron in the output layer will produce the maximum response, which is called the winning neuron—the position of the winning neuron changes with the type of input.

Before training, because the output neurons are randomly arranged, the position of the winning neurons corresponding to each input mode is uncertain.

In the training stage, a winning neighborhood is set with the winning neuron as the center. The weight vector connected by the neurons in the district is adjusted to the direction of the input vector according to the distance between the neuron and the winning neuron. The closer the winning neuron is, the greater the adjustment force is. The size of the superior neighborhood shrinks with the increase in training time. Through a lot of drills, the neurons in the output layer will become the sensory neurons of a specific pattern to

determine the corresponding relationship between the neurons in the output layer and the input pattern.

After training, the more similar the two inputs are, the closer the winning neurons are. Therefore, neurons can be divided into different regions according to their distance. Each region of the output layer corresponds to a known input type, and the corresponding core weight vector becomes the central vector of each input pattern class.

Because any dimensional vector will be compressed into two-dimensional data after SOFM and get a response in a certain area of the output layer, the network can integrate multiple obstacles into a case as the input of the web to realize the matching of dense obstacle environment.

5.2. Underlying Avoidance Algorithm. In this paper, the three-dimensional dynamic model is established based on the velocity and direction information of UAV and obstacle. It is used as the basis of collision prediction and bottom avoidance operation. The optimal bottom avoidance strategy can be summarized as the relative velocity vector of UAV, which minimizes the deviation between the old and new routes and tangents to the danger zone.

Next, we will demonstrate the strategy's correctness and the solution of the new speed in detail. Table 1 shows the meaning of some symbols.

Supposing that the initial time is t_0 , at t time after avoidance, the position offset vector of UAV and the original route is $\mathbf{S}'_o(t)$:

$$\mathbf{S}'_o(t) = \mathbf{S}_o(t_0) + \int_{t_0}^t \mathbf{V}'_o(t) dt. \quad (1)$$

If the adjustment is not carried out, the position vector $\mathbf{S}_o(t)$ of UAV at time $t_0 + t$ satisfies the following:

$$\mathbf{S}_o(t) = \mathbf{S}_o(t_0) + \int_{t_0}^t \mathbf{V}_o(t) dt. \quad (2)$$

$\therefore$ The position offset vector $\Delta \mathbf{S}_o(t)$ between UAV and the original route meets the following:

$$\Delta \mathbf{S}_o(t) = \mathbf{S}'_o(t) - \mathbf{S}_o(t) = \int_{t_0}^t \Delta \mathbf{V}_o(t) dt. \quad (3)$$

FIGURE 5: SOFM network training process: (a) initial distribution of the output layer; (b) the decay processing; (c) SOFM network after training.

TABLE 1: Initial symbol description.

Sign	Define
R	Velocity of UAV before adjustment
$\mathbf{V}_o$	The velocity of UAV after adjustment
$\mathbf{V}'_o$	UAV speed after adjustment
$\mathbf{V}$	The velocity of UAV relative to the obstacle
$\mathbf{V}'$	The velocity of UAV relative to obstacles after adjustment
$\mathbf{V}_r$	The velocity of obstacle
$\mathbf{S}(t)$	The position vector of UAV relative obstacle at time t
$\mathbf{S}_o(t)$	The position vector of UAV at time t

σ is used to represent the nearest distance between UAV and the obstacle.

$$\sigma = \frac{\mathbf{S} \cdot \mathbf{V}}{|\mathbf{V}|^2} \mathbf{V} - \mathbf{S}. \quad (4)$$

$\therefore$ The constraint condition of anticollision is as follows: after the UAV adjusts the motion state, the nearest relative distance between the UAV and the block is greater than the distance of the danger zone as follows:

$$|\sigma'| = |\mathbf{S}(t) + \Delta \mathbf{S}_o(t)| \geq R. \quad (5)$$

Furthermore, assume that both UAV and obstacles keep moving at a uniform speed when the system is avoiding obstacles. Equations (3) and (5) can be simplified as follows:

$$|\Delta \mathbf{S}_o(t)| = |\Delta \mathbf{V}_o|(t - t_0), \quad (6)$$

$$|\sigma'| = |\mathbf{S}(t_0) + \mathbf{V}'(t - t_0)| \geq R. \quad (7)$$

When t satisfies Equation (8), σ' reaches the mini-

mum satisfying Equation (9). Its principle is discussed by Han et al. [13].

$$t = \frac{\mathbf{S}(t_0) \cdot \mathbf{V}'}{|\mathbf{V}'|^2}, \quad (8)$$

$$|\sigma'| = |\sigma'|_{\min} = R. \quad (9)$$

$\therefore$ The optimal avoidance strategy of UAV is the minimum velocity offset required to make the nearest relative distance between UAVs and obstacles equal to the radius of the danger zone. It is shown in

$$\begin{aligned} \min |\Delta \mathbf{V}_o| \\ \text{s.t. } |\sigma'| = R. \end{aligned} \quad (10)$$

Assume that the angle between the relative velocity $\mathbf{V}$ and the adjusted speed $\mathbf{V}'$ of UAV is β according to the vector projection rule. The minimum value of $|\Delta \mathbf{V}_o|$ satisfies

$$|\Delta \mathbf{V}_o|_{\min} = |\mathbf{V}| \sin \beta. \quad (11)$$

$\therefore$ Equation (8) can be further simplified as

$$\begin{aligned} \min \beta \\ \text{s.t. } |\sigma'| = R. \end{aligned} \quad (12)$$

Considering the existence of the danger zone, we can simplify the UAV and the obstacle into a particle and record the line between the two points as the S axis. We record the cone as “ N ,” whose vertex is UAV and the generatrix is at the angle of $\eta = \arcsin(R/|S|)$ the S axis. The intersection line of “ N ” and the hazard zone is marked as “ M .”

It is easy to prove that at any point on the “ M ,” a velocity vector tangent to the dangerous area of the obstacle can be determined. When the angle β is the smallest, the relative velocity $\mathbf{V}'$ and the tangent point D of the hazardous area

FIGURE 6: Optimal avoidance speed. It shows how to deduce the new velocity.

are on the plane where $\mathbf{V}$ and $\mathbf{S}$ are located, as shown in Figure 6.

According to Figure 6, the following conclusions can be drawn.

- (1) If the velocity vector and position vector are in different directions, the velocity of UAV after adjustment satisfies

$$\mathbf{V}'_o = \frac{\mathbf{V} \cos(\eta - \varepsilon)}{\sin \varepsilon} [\sin \eta \cdot \mathbf{V} - \sin(\eta - \varepsilon) \cdot \mathbf{S}] + \mathbf{V}_r. \quad (13)$$

- (2) If the velocity vector and the position vector are in the same direction, their plane loses uniqueness. The algorithm needs to randomly adjust the velocity and recalculate again

In practical application, the movement state of obstacles may change rapidly in a short time. Therefore, for safety reasons, the collision prediction needs to be carried out again after obstacle avoidance adjustment. If the relative velocity direction of the UAV no longer intersects with the danger zone, we think the avoidance is effective.

5.3. Self-Development Algorithm. This paper mainly uses deep learning in two places. One is the matching module mentioned above through the SOFM network, and the other is the content of this section. An autonomous development algorithm based on deep learning, as shown in Figure 7, is used to supplement the knowledge base. It includes a feature extractor, development body, and knowledge storage as discussed elsewhere [14, 15]. In this algorithm, firstly, the feature vector of the peril is extracted by the feature extractor, and the matching failure obstacle is regarded as a new sample. Then, the development body stores the case and the corresponding strategy function. Finally, the hash mapping between the patient and the strategy is established by the hash table.

Next, take C++ as an example to illustrate how to establish the “hash mapping” based on the hash table:

Define a separate map using the STL map container.

```
map<Case, Strategy>mp;
```

The case type is defined by the declaration (generally the structure type that encapsulates the data). The strategy type is the corresponding policy type (generally, the function pointer type).

In this way, the “case type” mapping to the “strategy type” is established. A mapping library is specified by assigning the key and values in the map. When the <case, strategy> mapping library is called later, an iterator can be defined.

```
Case CaseN;
```

```
Map<Case, Strategy>::iterator it = mp.find(CaseN);
```

Return the iterator of the mapping with key casein and pass.

```
Strategy *StrategyN = it->second;
```

Therefore, the corresponding policy function pointer is obtained, and the SAS can call the processing function.

6. Design of ADS-B Receiver Integrated with RF and Baseband

This paper adopts the ADS-B communication system based on the satellite platform to replace radar, which takes the satellite platforms as the base station. If UAV sends its own position, motion status, and other information to the satellite base station, the satellite platform will quickly calculate a large range of real-time safe routes depending on its advantages [10–12]. Because the UAV is only responsible for sending and receiving information through the ADS-B transceiver, it greatly reduces the computation of the UAV and no longer needs airborne radar.

Naturally, a qualified ADS-B transceiver becomes the most important. The traditional satellite-based ADS-B technology is not suitable for large-scale promotion because of its large volume, high power consumption, and low reliability. The single beam of a typical satellite platform has a width of about 2000 km from the ground. The detection probability is greatly reduced due to signal conflict in the area with dense aircraft.

To solve the above problems, the ADS-B receiver based on the phased array shown in Figure 8 is adopted in this paper. The receiver adopts an RF baseband-integrated chip, which dramatically reduces the complexity of the RF channel. At the same time, the ultra-high resource FPGA required for parallel demodulation of multichannel signals is used to realize interface conversion by using CPLD with small resources without embedded FPGA. There are L-band RF channels on both sides of the receiver. The beams are synthesized by seven rays at the load RF front end, and each shaft is allocated to an RF channel for amplification, downconversion, and ADC.

7. Simulation Test of the Obstacle Avoidance Algorithm

This paper builds the UAV system simulation environment through MATLAB to verify the efficiency and correctness

FIGURE 7: Autonomic development model.

FIGURE 8: Radiofrequency integrated satellite-based ADS-B transceiver: (a) compatible GPS-LI/BD-BI receiver chip layout; (b) frequency synthesizer—precise locking and tracking.

FIGURE 9: The relative distance between UAV and obstacle.

of the bottom avoidance algorithm, assuming that the obstacles are moving at a uniform speed. According to the FAA standard, this paper takes that the distance of the dangerous area is 150 m. When the UAV predicts a collision, it adjusts the motion state through the underlying algorithm. As shown in Figure 9, the relative distance between the two is still higher than the boundary of the danger zone when they are closest. The simulation results show that the underlying avoidance algorithm of the SAS can avoid a sudden obstacle.

Then, we test the avoidance performance of the SAS in a dense obstacle environment. The results are shown in Figure 10. We set multiple random barriers in MATLAB and compare the results of different algorithms. They show

FIGURE 10: Obstacle avoidance trajectory of UAV with different algorithms.

that the SAS can make the UAV pass safely in an environment with dense obstacles.

8. Conclusions

In this paper, the UAV avoidance system is divided into two parts: the LAS and the SAS. The cooperation between them

can make UAVs navigate safely in the complex environments. For example, the LAS can reduce the workload of the SAS, while the SAS provides fault tolerance for the LAS.

The LAS is mainly responsible for safe route planning, putting the task of route planning on the satellite platform. Therefore, the UAV only needs to be equipped with an ADS-B transceiver and decoding circuit, reducing the calculation of UAV significantly. Compared with radar, the price of the ADS-B receiver is lower, which can save the economic cost of UAVs and is more suitable for civil UAVs.

The SAS is mainly responsible for evading the sudden short-range obstacles around the UAV through deep learning. It has many advantages. The system can directly use the existing strategy after matching without going through the underlying algorithm operations. It can also realize the direct mapping of obstacle samples and solutions saving search time compared with the traditional developmental learning mechanism, which needs complex retrieval.

In general, the system proposed in this paper can greatly reduce the computation of UAV, improve the reaction speed, increase the fault tolerance rate, and reduce the production cost.

Data Availability

The raw data used to support the findings of this study have been deposited in the website (<https://github.com/1578840588/A-Design-of-Avoidance-System-for-UAV>).

Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

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References

- [1] R. Bo, Z. Tao, and Y. Lei, "Study on path planning for aircraft based on improved A* algorithm," *Systems Engineering and Electronics*, vol. 30, no. 2, pp. 324–326, 2008.
- [2] W. A. N. G. Dianjun, "Indoor mobile-robot path planning based on an improved A* algorithm," *Journal of Tsinghua University (Sci and Tech)*, vol. 52, no. 8, pp. 1085–1089, 2012.
- [3] Z. H. A. O. Wenting and P. E. N. G. Junyi, "VORONOI diagram-based path planning for UAVs," *Journal of System Simulation*, vol. 18, no. 2, pp. 159–162, 2006.
- [4] Y. E. Yuanyuan, M. I. N. Chunping, S. H. E. N. Lincheng, and W.-s. Chang, "VORONOI diagram based spatial mission planning for UAVs," *Journal of System Simulation*, vol. 17, no. 6, pp. 1353–1355, 2005.
- [5] B. Vanek, T. Peni, J. Bokor, and G. Balas, "Practical approach to real-time trajectory tracking of UAV formations," in *Proceedings of the 2005, American Control Conference, 2005*, pp. 122–127, Portland, OR, USA, 2005.
- [6] O. Khatib, "Real-time obstacle avoidance for manipulators and mobile robots," *The International Journal of Robotics Research*, vol. 5, no. 1, pp. 90–98, 1986.
- [7] R. Simmons, "Structured control for autonomous robots," *IEEE Transactions on Robot and Automation*, vol. 10, no. 1, pp. 34–43, 1994.
- [8] R. Brooks, "A robust layered control system for a mobile robot," *IEEE Transactions on Robot and Automation*, vol. 2, no. 1, pp. 14–23, 1986.
- [9] G. SANDINI, G. METTA, and D. VERNON, "Robot cub: an open frame work for research in embodied cognition," in *4th IEEE/RAS International Conference on Humanoid Robots, 2004*, pp. 13–32, Santa Monica, CA, USA, 2004.
- [10] Z. Shibo, *Research on the Method of Route of Planning Aircraft Based on ADS-B*, Hebei University of science and technology, 2017.
- [11] D. Songtao, L. Haitao, and L. Baoguo, "Design and implementation of satellite based ADS-B system simulation software," *Intelligent computer and application*, vol. 9, no. 3, pp. 23–28, 2019.
- [12] R. Pengfei, *Design of 1090ES Mode ADS-B Signal Receiver*, Harbin Engineering University, 2014.
- [13] H. Tong, Z. Huan, L. Xia, W. Xingwei, and H. Luo, "Autonomous collision avoidance control of UAV against non-cooperative dynamic obstacles," *Electronics Optics & Control*, vol. 2017, no. 2, pp. 6–12, 2017.
- [14] W. Ruixuan, Z. Qirui, and Z. Xu, "A brain-like mechanism for developmental UAVs' collision avoidance," *Control Theory & Applications*, vol. 36, no. 2, pp. 175–182, 2019.
- [15] C. Xiangzhang, Y. Zhihao, and C. Zesu, "Development model of autonomous developing robots with independent environmental cognition," *Journal of PLA University of Science and Technology (Natural Science Edition)*, vol. 14, no. 5, pp. 507–510, 2013.