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Monte Carlo Simulation-Based Risk Assessment for Unmanned Ground Equipment Taxiing Guidance

Qing Zhao[1,a], Tianxiong Zhang[1,b], Dezhou Yuan[1,c], Xinping Zhu[1,d,*]

[1]Air Traffic Management College, Civil Aviation Flight University of China, No. 46, Section 4, Nanchang Road, Guanghan, Sichuan, China

[a]qing_zhao_business@foxmail.com, [b]tianxiongzhang@cafuc.edu.cn, [c]ftu9275@163.com, [d]zxp@cafuc.edu.cn

[*]Corresponding author

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Abstract: Due to the potential safety hazards such as incorrect or missed aircraft guidance caused by human-operated guiding, the introduction of unmanned guiding vehicles can effectively reduce these unsafe events. However, the risks associated with unmanned driving guiding vehicles in the process of guiding aircraft taxiing have not yet been thoroughly and quantitatively studied. This paper collects the kinematic parameters of the unmanned driving guiding vehicle during the process of guiding manned aircraft, applies Monte Carlo simulation to generate a dataset of simulated operational processes that cover the entire taxiing guidance process, and introduces three major risk assessment indicators based on the motion process between the unmanned driving guiding vehicle and the manned aircraft during the taxiing guidance process. Through the normalization function of risk evaluation indicator weights and based on the Gaussian distribution that satisfies the normal distribution, a qualitative evaluation of risk levels is conducted based on quantifiable actual operational processes. The results show that quantifiable risk assessment indicators can provide risk evaluation results with stronger real-time reference and offer operable solutions for risk avoidance.

1. Introduction

The rapid advancement of unmanned driving technology has brought about revolutionary changes in the field of transportation. With the increasing application of unmanned vehicles, the associated safety risks have garnered significant attention. Scientific and systematic assessment of these risks is crucial for ensuring the sustainable development of unmanned driving. Preliminary exploration and application of this technology within airports have already commenced[1]. This paper investigates the safety risk assessment methods for unmanned Ground Support Equipment (GSE) operating within airports.

The rise of unmanned driving technology has brought unprecedented opportunities and challenges to the transportation sector. However, like any emerging technology, unmanned driving faces a series of potential risks that require comprehensive assessment to ensure its safety and reliability.

The assessment of safety risks in vehicle and aircraft operations is key to evaluating the level of airport surface resource utilization. The current risk indicators applied to vehicle traffic include the following four categories:

- Kinematic-based indicators, such as vehicle acceleration[2]. Washington et al. [3] proposed a two-dimensional risk rating model based on vehicle speed and collision distance.
- Data-based risk assessment models, such as Gaussian distribution accident rate risk assessment models constructed from data[4]. Bagschik G et al.[5] conducted statistical classification analysis of various unmanned vehicle driving risks based on existing experimental results.
- Potential field-based risk assessment models. Dursun M et al.[6] proposed the safety potential field theory, introducing acceleration parameters to improve the existing safety potential field model, depicting the changes in vehicle safety potential fields at different speeds and accelerations.
- Indicators based on the time of motion change, such as Time to Collision (TTC), Time to React (TTR), and Post Encroachment Time (PET). Many car manufacturers have applied the TTC indicator to their advanced driver-assistance systems for emergency braking, but considering the significant differences in perception and motion state changes between unmanned and human-driven vehicles, human factors such as TTR are not suitable for studies on the safety analysis of unmanned vehicles.

The safety risk indicators for aircraft operations mainly include the following three categories: 1) Actual on-site video detection analysis. Tianxiong Zhang et al.[7-8] implemented airfield aircraft video surveillance analysis through machine learning, evaluating aircraft encounter risks through wingtip distance. 2) Risk calculations considering the taxiing state of aircraft. Primatesta S et al.[9] integrated factors such as aircraft taxiing length, engine jet blast, and fuselage length to construct a conflict risk quantification model. Additionally, when aircraft operate mixed with other targets, the spatial ranges of aircraft models, nose protection areas, and wingtip safety zones must be considered for their impact on safe operation, to avoid property damage due to inadequate target detection during aircraft operation[10].

In the operation of unmanned vehicles, perception devices are affected by weather on radar reflectivity and the reduced level of target detection by cameras in low visibility[11]. Shalev-Shwartz et al.[12] proposed that traditional human-driven vehicles place high demands on drivers, and due to long reaction times and traffic disruptions, they explored the possibility of improving road traffic flow with unmanned vehicles combined with computer vision technology to reduce costs and average waiting times for vehicles in certain areas. Unmanned driving technology is expected to significantly improve traffic safety, traffic monitoring, and highway infrastructure management costs[13]. Elmahjub E et al.[14] discussed the transformative extraction of key features from videos and images obtained by computer vision algorithms, as well as improvements in traffic flow analysis methods, risk assessment, accident investigation, and road damage assessment. However, the obstacles faced by the large-scale deployment of unmanned vehicle cooperative operation technology are complex and interrelated, and strategies to overcome these obstacles and their impacts also need to be addressed[15-17].

In summary, while there is extensive research on vehicle and aircraft conflict detection and risk assessment methods, studies considering the mixed operation of unmanned vehicles and human-piloted aircraft within airport environments are scarce. The main reason is the significant differences in their operational processes, and sometimes risk assessment indicators need to consider driver and vehicle characteristics. However, considering both sets of operational indicators separately results in an extensive and unclear evaluation content[18]. For example, considering potential fields and other studies that can disregard the characteristics of the vehicle-aircraft themselves, the methods of integrating environmental information are complex and make it difficult to effectively visualize the results of multi-target risk assessments[19]. Therefore, this paper starts from the operational scenario of unmanned guidance vehicles implementing human-piloted aircraft within the airport environment and proposes a multi-source information risk assessment model for vehicle-aircraft. By integrating vehicle perception and aircraft pilot observation information, combined with cloud-based vehicle and aircraft operation information, the mixed operation risks of vehicles and aircraft are graded, providing references and ideas for ensuring the safe mixed operation of unmanned vehicles and aircraft.

2. Manuscript Preparation

2.1. Risk Assessment Logic

The risk assessment logic is based on the motion states of unmanned guidance vehicles and human-piloted aircraft completing taxiing guidance tasks on airport taxiways. The study focuses on the unmanned guidance vehicle and the aircraft block as the research subjects. The aircraft block includes the aircraft itself and the effect area generated by the engine jet blast of the aircraft. The scope of the aircraft block is illustrated in Figure 1.

Unmanned guidance vehicles, relying on their state perception modules and using vehicle perception data as a condition, combine this with the actual motion scenario to arrive at vehicle motion decision-making results. The execution process of vehicle motion is reflected in the changes in state evaluation indices such as vehicle speed, acceleration, throttle, and brake. In the previously established scenario of executing guidance tasks, vehicles can independently judge the surrounding environment and obstacles and make corresponding decisions. Based on the changes in vehicle motion state after decision-making, the distribution of motion states for both vehicles and aircraft is presented. By employing quantifiable risk assessment indicators, the risk levels of guidance tasks are defined, enabling the quantification of risks during the motion process between unmanned guidance vehicles and human-piloted aircraft.

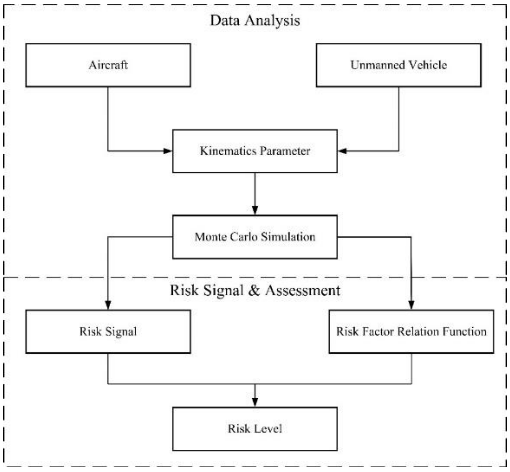

Figure 1: Technology Roadmap

As depicted in Figure 1, the risk assessment technology roadmap of this paper is divided into three main parts: Unmanned Vehicle & Manned Aircraft Operation Stage, Data Analysis, and Risk Signal & Assessment.

(1) Unmanned Vehicle & Manned Aircraft Operation Stage: This stage primarily investigates the replication of motion control functions of unmanned vehicles and the manned operation processes of aircraft within the airport. The functionality of unmanned vehicles is achieved using completed automatic control modules for target detection and motion trajectory tracking.

• Aircraft Simulation: In experiments, it is necessary to collect data on the motion processes of preceding aircraft that affect the operation of unmanned vehicles. Using P3D aircraft simulation software, the motion processes of manned aircraft operating within the airport are tracked, ultimately providing information on the aircraft's speed and position throughout the airport.

• Unmanned Vehicle Simulation: After integrating automatic control functions into the unmanned vehicle, it is assumed that the vehicle will follow the preceding aircraft. The unmanned vehicle's sensors perceive the manned aircraft ahead and track the set path accordingly. During this process, motion data of the unmanned vehicle affected by the preceding manned aircraft is collected.

(2) Data Analysis: This stage focuses on collecting kinematic parameter data of unmanned vehicles when they follow manned aircraft operating within the airport. Due to the limited number of experiments, it is not possible to accurately evaluate the actual motion states during repeated operations; therefore, Monte Carlo simulation is used to perform data-based simulation of the obtained scenario parameters.

• Kinematics Parameter: The obtained speeds and accelerations of the unmanned vehicles, as well as the distance to the preceding aircraft, are taken as reference values to determine the kinematic parameters of the unmanned vehicles when influenced by the preceding aircraft.

• Monte Carlo Simulation: Based on the obtained kinematic parameter values, data-driven Monte Carlo simulation is conducted on the motion process, with the objective of validating the experimental results under the premise of existing data and random distribution of motion outcomes, to enhance the accuracy of the results.

(3) Risk Signal & Assessment: This stage investigates the motion states that must be maintained for safe operation based on the obtained data. By establishing Risk Signals, Risk Factor Relation Functions, and Risk Level classifications, the risk levels under the scenarios set forth in this paper become quantifiable indicators.

• Risk Signal: Using the kinematic parameters obtained from previous steps, corresponding risk assessment indicators are defined to calculate risk levels from different dimensions, making risk quantifiable and providing a reference threshold.

• Risk Factor Relation Function: As there are variations in the parameters required to achieve the target motion state during perception and decision-making by unmanned vehicles, the established risk assessment indicators differ in their ability to measure operational risks. Hence, corresponding weight relation functions are introduced to make the obtained risk thresholds more referential.

• Risk Level: Based on the obtained risk indicators and the calculated distribution thresholds, risk levels for different states are classified through the weight relation function. The risk levels obtained define the riskiness and, based on the scenario risk levels, adaptive monitoring is conducted for the corresponding scenarios.

2.2. Definition of Risk Boundaries

During the experimental process, the perception range of the unmanned guidance vehicle for detecting targets ahead is modeled as an arc. This arc shape is not achievable in actual target detection but can be statistically accounted for through vehicle-aircraft-cloud data integration. The engine thrust power in breakaway mode dictates that the exhaust risk zone radius is approximately 1.67 to 2 times the length of the aircraft body. For ease of calculation, twice the body length is uniformly adopted as the radius of the exhaust range, with the center at the nose of the aircraft and an arc of 45 degrees. The simplified arc column center of the aircraft lies on the extension line of the engine exhaust danger zone, assumed to be at the nose, thus the arc radius is twice the body length, and the vehicle's detection range of the aircraft is a sector-shaped column. The pilot's observation of the unmanned vehicle is a rectangular prism, with the observation point at the nose of the aircraft, disregarding the distance between the cockpit and the nose. The pilot's field of view is arc-shaped, and the distance obtained when the unmanned guidance vehicle tangentially intersects with the observation arc is considered the observation distance, as shown in Figure 2.

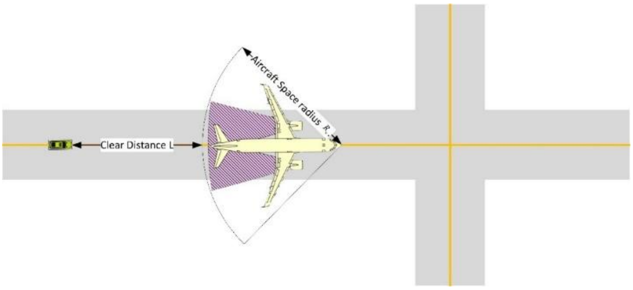

Figure 2: Simplified Schematic of Unmanned guidance vehicle and Preceding Aircraft Perception

The distance at which the front of the unmanned guidance vehicle tangentially intersects with the tail arc of the guide unit is considered the clear distance. When the preceding guide unit performs maneuvers, such as turning, the impact of the irregular configuration of the aircraft's tail on the following unmanned vehicle is not considered. As the aircraft pilot visually follows the unmanned guidance vehicle ahead, due to the significant difference in individual specifications, there is no need to optimize the vehicle ahead into an arc shape. Instead, only the shortest distance between the longitudinal centerline of the vehicle intersecting with the rear of the vehicle and the position of the aircraft's nose is considered, and this distance is defined as the clear distance L between the vehicle and the aircraft. Furthermore, when the aircraft turns at taxiway intersections, the simplification to a sector-shaped arc allows for the disregard of differences in the turning process compared to straight-line motion, reducing the occurrence of high-risk events due to changes in motion states.

In actual driving scenarios, considering that the aircraft lacks autonomous path decision-making capabilities, the pilot's reactive response to stimuli from other aircraft ahead or entities unrelated to the guidance task during taxiing is not considered. That is, the aircraft is only influenced by the motion state of the unmanned guidance vehicle implementing the taxiing guidance task ahead.

2.3. Monte Carlo Simulation

To investigate the risk association between unmanned vehicles and perceived targets, only the influence of perceived targets on the motion process of unmanned vehicles is considered. The aim is to replicate potential changes in the vehicle's motion states exponentially based on limited data, ultimately achieving accurate judgment of risk assessment results.

This paper employs Monte Carlo simulation, focusing on the speed of unmanned vehicles as the experimental subject, to statistically test scenarios that may compromise airport safety due to extreme conditions such as inadequate vehicle perception equipment.

The simulation generates random numbers within an interval that follow a Gaussian distribution with a mean (μ) representing the clear distance and a standard deviation (σ), with the distribution function expressed as follows:

$$X_i = \mu + \sigma Z_i \tag{1}$$

Where X_i is the value of the random variable obtained in the ith simulation; μ is the mean of the Gaussian distribution, representing the average level of the random variable; σ is the standard deviation of the Gaussian distribution, representing the range of fluctuation of the random variable; Z_i is the ith random number drawn from the random variables that follow the Gaussian distribution.

When the unmanned vehicle does not perceive a target, the vehicle's motion process remains unchanged, and no motion state decision is made. If the unmanned vehicle perceives a preceding aircraft that impacts safe operation, it will make and execute a risk mitigation decision. If the unmanned vehicle detects that risk mitigation actions are insufficient to ensure safe operation, it will adopt an aggressive motion decision strategy. Such an incident is defined as a high-risk event.

2.4. Selection of Risk Indicators

2.4.1. Full Velocity Difference between Unmanned guidance vehicle and Aircraft

During the process of guiding aircraft, the lateral and longitudinal motion decisions of the unmanned guidance vehicle are derived from the vehicle's embedded lateral and longitudinal control modules. The lateral control module is influenced by the vehicle's position, performance, and parameters. Longitudinal control considers the impact of the vehicle's own power output, rotational speed, and torque, with the changes in these parameters ultimately reflected in the engine speed, vehicle velocity, and acceleration. The motion changes of manned aircraft are not only related to the aircraft engine thrust and control system type but are also affected by unstable factors such as the pilot's mental state and the distance to targets ahead. Considering the diversity of aircraft types, the uncertainty of pilot human factors, and the complexity of quantification, the difference in operation between the two is quantified solely in terms of velocity, with the calculation expressed as follows:

$$\Delta v = \sqrt{(\Delta v_x)^2 + (\Delta v_y)^2} \tag{2}$$

Where Δv_x, Δv_y represent the velocity differences of the two objects in the x and y directions, respectively. This formula calculates the Euclidean norm of the velocity vectors of two objects in three-dimensional space.

In multi-target conflict analysis, the full velocity difference can be used to assess the speed changes in the motion of consecutive targets. Since the full velocity difference conveys directional information and the operating speeds of vehicles and aircraft within the airport are approximately similar, a sharp increase in the full velocity difference can indicate a significant difference in the direction of motion between the target and the subject.

2.4.2. Expected Control Time

The Expected Control Time (ECT) is calculated based on the motion state of the target and the interference from the target ahead, within the context of their state intervention space. It estimates the time it might take for the two entities to come into spatial contact due to uncontrollable factors. If the time to spatial contact is less than the permissible threshold set by relevant regulations and does not meet risk avoidance conditions, the risk level is independently categorized, and the uncontrolled target is required to cease movement immediately under the simulated conditions. The formula for calculating the Expected Control Time is as follows:

$$T = \begin{cases} -\dfrac{L}{\Delta v} & \Delta v < 0, \Delta a = 0 \\ \dfrac{-\Delta v - \sqrt{\Delta v^2 - 2\Delta a L}}{\Delta a} & \Delta v < 0, \Delta a \neq 0 \\ \dfrac{-\Delta v + \sqrt{\Delta v^2 - 2\Delta a L}}{\Delta a} & \Delta v \geq 0, \Delta a < 0 \end{cases} \tag{3}$$

Where T represents the Expected Control Time, L is the clear distance between the consecutive targets, Δv is the relative velocity between the targets, Δa is the relative acceleration between the targets, and Δs is the relative motion distance between the targets.

2.4.3. Minimum Expected Clear Distance

In the mixed operation of unmanned guidance vehicles and aircraft on the airfield, the aircraft pilot visually follows the guidance vehicle while taxiing within the airport from the cockpit.

Based on the decision-making and execution process of the unmanned vehicle, the relationship between vehicle speed and motion distance can be derived. The motion change distance of the aircraft is as follows:

$$\begin{aligned} d_p &= v_p t_1 + \int_0^{t2} (v_p - \frac{a_p}{2t_2} t^2) dt + (v_p - \frac{1}{2} a_p t_2) t_3 - \frac{a_p}{2} t_3^2 \\ &= v_p (t_1 + t_2 + t_3) - \frac{a_p}{6} (t_3^2 + 3t_2 t_3 + 3t_3^2) \end{aligned} \tag{4}$$

$$t_3 = \frac{v_p}{a_p} - \frac{1}{2} t_2 \tag{5}$$

Where v_p is the operating speed of the preceding target aircraft, a_p is the acceleration of the aircraft, t_1 is the delay duration of the aircraft's motion change operation, t_2 is the duration of the aircraft's stable braking, and t_3 is the duration from stable braking until the aircraft's speed reaches zero. During this period, the unmanned vehicle should maintain a motion state similar to that of the aircraft to ensure a safe distance between them.

Due to the sensitive perception and rapid decision-making execution of unmanned vehicles, the braking process can be simplified, and the braking distance is as follows:

$$d_c = \frac{v_c^2}{2a_c} \tag{6}$$

Furthermore, when the target ahead is not an aircraft, the calculation formula for d_p can be simplified as follows:

$$d_p = \frac{v_v^2}{2a_v} \tag{7}$$

Where v_v is the operating speed of the non-aircraft target ahead, and a_v is the acceleration of the non-aircraft target.

Combining (5) and (7), the minimum expected clear distance between unmanned guidance vehicles and the target ahead within the airport can be determined as:

$$d_s = d_c - d_p + d_{\min} \tag{8}$$

Where d_s is the minimum expected clear distance; $d_{\min}$ is the minimum safety interval between vehicles and aircraft within the airport, typically set at 50 meters.

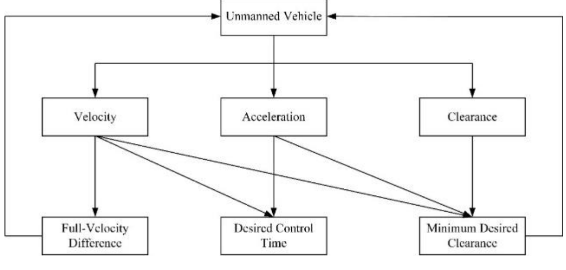

Figure 3: Schematic Diagram of the Relationship between Vehicle Characteristic Parameters and Risk Indicators

As shown in Figure 3, the unmanned vehicle, equipped with automatic control functions, calculates the three set risk assessment indicators—full velocity difference, expected control time, and minimum expected clear distance—based on three kinematic parameters: vehicle motion speed, vehicle acceleration, and the clear distance between the vehicle's front and the preceding aircraft. The calculation of the full velocity difference only considers the impact of the velocity difference between the vehicle and the aircraft, while the expected control time must consider not only the vehicle's motion speed but also the changes in vehicle performance and motion state during acceleration and deceleration. The calculation of the minimum expected clear distance requires the unmanned vehicle's speed, acceleration, and the clear distance to the detected target. The final calculated full velocity difference and minimum expected clear distance will directly feedback to the unmanned vehicle and influence its subsequent motion state.

3. Experimental Result

In accordance with airport operational service rules, the average speed of the unmanned guidance vehicle during guidance tasks is set at 21.6 km/h (6 m/s), following a normal distribution with a mean (μ) of 21.6 and a standard deviation (σ) of 2, serving as the vehicle's initial speed. Assuming the vehicle travels at an average speed under normal conditions, it responds with appropriate speed changes upon perceiving a target ahead. A single-target scenario was generated 100 times, with a data collection interval of 1 ms. The vehicle's lateral speed changes are solely related to the path and do not consider emergency maneuvers such as lane changes to avoid targets ahead.

Monte Carlo simulation was used to categorize and statistically analyze the indicators obtained from the experimental scenario. The resulting curve of the unmanned vehicle's decision-making process speed changes is shown in Figure 5. The vehicle's transition from stop to acceleration to constant speed is not entirely nonlinear or satisfying a specific curve equation, and there may be brief transient processes. During deceleration, the vehicle's speed change process generally does not experience transients. The maximum speed fluctuates within the range of 16 km/h to 26 km/h, which is consistent with the actual motion process of unmanned guidance vehicles in various lanes and sections within the airport environment. When the vehicle's speed is close to that of the target ahead, and the speed difference exceeds the average operating speed difference between vehicles, it can be considered that there is a certain risk in the operating speed. Conversely, if the average speed under this speed difference can be maintained, it is deemed safe.

Based on the influence distance of aircraft jet blast on targets behind and the perception capabilities of unmanned vehicles, Monte Carlo simulation was conducted to simulate the tracking distance of unmanned vehicles, resulting in a vehicle distance maintenance distribution graph, as shown in Figure 4.

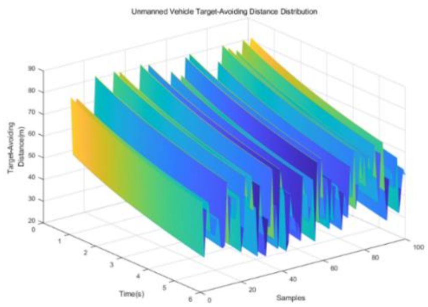

Figure 4: Distribution Graph of Proactive Decision-Making Safety Distance for Unmanned vehicles

The frequency of unmanned vehicles maintaining a safe clear distance was statistically analyzed, as shown in Figure 5. The vehicle's maintained distance ranges from 30 meters to 90 meters, with a concentration in the 40 to 80-meter range. Particularly when the distance is less than 40 meters, the frequency of occurrence significantly decreases, indicating that this range is not conducive to the safe driving of unmanned vehicles. When the distance is greater than 90 meters, due to the complexity of the airport's runway and taxiway structure, larger safety distances are not considered as samples for measuring vehicle safety distance.

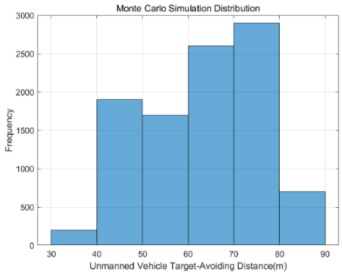

Figure 5: Frequency Graph of Safe Clear Distance for Unmanned vehicles

Vehicles are subject to a certain degree of decision response error due to the influence of onboard perception equipment and the signal transmission process. This primarily affects the difference between the vehicle's theoretical motion state and the actual motion process. The obtained response density distribution graph is shown in Figure 6. The majority are greater than 0.1 seconds and less than 0.2 seconds, with the density distribution greater than 0.5 seconds being negligible. This paper only considers the impact of the unmanned vehicle's motion process on the safety of vehicle operation.

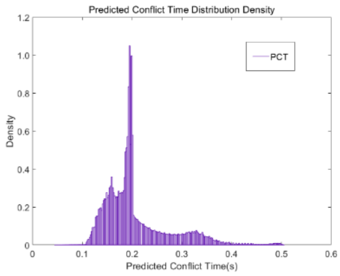

Figure 6: Decision Response Density Distribution for Unmanned vehicles

As calculated previously, the median safe distance for vehicles was found to be 84.32 meters, indicating that the distance between vehicles is often maintained at the aforementioned distance. By calculating the 5th percentile of the Gaussian distribution, the vehicle distance was found to be 50.13 meters, yielding the minimum conflict distance value. The box plot of the safe distance and predicted conflict distance is shown in Figure 7.

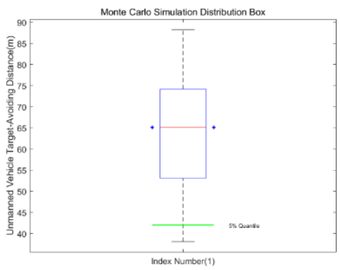

Figure 7: Box Plot of Safe Distance Distribution

Considering the behavior and risk assessment indicators of unmanned vehicles operating within the airport, the risk levels for ensuring the operation of ground support equipment under different scenarios were determined, as shown in Table 1.

Table 1: Vehicle Operation Risk Assessment Strategy

Full Velocity Difference (m/s)	Expected Control Time (s)	Minimum Expected Clear Distance (m)	Operational Risk Level
$\Delta v < 0.25v$	$T > T_r$	$d_s > d_m$	Low Risk
		$d_r \le d_s \le d_m$	High Risk
		$d_s \le d_r$	High Risk
	$T < T_r$	$d_s > d_m$	Low Risk
		$d_r \le d_s \le d_m$	Medium Risk
		$d_s \le d_r$	High Risk
$\Delta v \ge 0.25v$	$T > T_r$	$d_s > d_m$	High Risk
		$d_r \le d_s \le d_m$	High Risk
		$d_s \le d_r$	High Risk
	$T < T_r$	$d_s > d_m$	Medium Risk
		$d_r \le d_s \le d_m$	High Risk
		$d_s \le d_r$	High Risk

4. Conclusion

The purpose of this study was to conduct high-precision simulations of the automatic control functions of unmanned vehicles and the motion processes of manned aircraft, with reference to the technical requirements of airport autonomous equipment and related airport operational service principles. Based on relevant literature, this paper proposes a risk assessment scheme for unmanned vehicles in scenarios where there is a significant difference in motion processes compared to aircraft. Unmanned vehicles achieve the reconstruction of the electric unmanned vehicle dynamics model under automatic control algorithms, with Carsim used to output and monitor vehicle dynamic performance. The operational behavior of unmanned vehicles in mixed operation with aircraft within the airport was objectively discussed, based on the known motion processes of manned aircraft.

This paper employed a quantitative analysis method based on Monte Carlo simulation, simulating the motion parameters such as speed of unmanned vehicles during operation, to define risk indicators and categorize risk levels for scenarios where unmanned vehicles follow aircraft. The results indicate that the full velocity difference and minimum expected clear distance have a significant impact on the risk level of unmanned vehicles operating within the airport. When the speed of unmanned vehicles is controllable and the clear distance between perceived targets is within a reasonable range, other perceived targets do not pose a threat to driving safety. However, high-risk events may occur in certain scenarios due to the limitations of perception distance, necessitating improvements in vehicle hardware conditions.

The paper validates the feasibility of the unmanned vehicle dynamics model by constructing an automatic control module based on vehicle characteristics. High-reliability scenario restoration verification of aircraft motion processes is achieved using simulation operation data from manned aircraft. This research aims to provide a viable reference scheme for subsequent definitions and considerations of risks associated with the operation of unmanned vehicles within airports.

Nevertheless, due to the uncertainties in coordinate transformation and multi-target mixed operation processes within the system, it is not possible to synchronize the motion behavior of fully unmanned vehicles with the piloting process of aircraft, which is one of the limitations of this study. Therefore, by collecting scenarios where manned aircraft determine that unmanned vehicles ahead affect the operation of the aircraft, it is possible to identify the three major risk assessment indicators for aircraft motion within the airport, evaluate the risk level of aircraft in complex operational scenarios, and define risk events. Using Monte Carlo simulation to fit experimental data, the risk level distribution of manned aircraft in risk scenarios under large sample data is obtained, providing a viable solution for subsequent risk indicator corrections.

In the future, with the introduction of more unmanned vehicles within airports, it will be necessary to combine the differences in the dynamic performance of different ground support equipment to differentially evaluate risk indicators in complex scenarios, and to confirm the risk scenario level categorization decisions for such vehicles or various types of aircraft to ensure safe operation.

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