

# **Autonomous Navigation and Obstacle Avoidance of UAVs Based**<br> **Autonomous Navigation and Obstacle Avoidance of UAVs Based**<br> **Autonomous Navigation and Obstacle Avoidance of UAVs Based<br>
on Deep Reinforcement Learning<br>
Xinyu FREE Academic Education**<br>
Signal Development<br> **on Deep Reinforcement Learning**<br> **on Deep Reinforcement Learning**<br>
Xinyuan Wang\*<br> *Corresponding author*<br> *Corresponding author* **Xinyuan Wang**<br> *Mutonomous Navigation and Obstacle Avoidance of UAVs Based*<br> **Autonomous Navigation and Obstacle Avoidance of UAVs Based<br>
on Deep Reinforcement Learning<br>
Xinyuan Wang<sup>\*</sup><br>** *Department of Transportation, Nan* **Examplement**<br> **4)**<br> **and Obstacle Avoidance of UAVs B:<br>
<b>Reinforcement Learning**<br>
Xinyuan Wang\*<br> *g University of Aeronautics and Astronautics, Nanjing,*<br>
\**Corresponding author*<br> **i**, the developed within logistics, agri

International Conference on Social Development<br>
and Intelligent Technology (SDIT2024)<br> **Autonomous Navigation and Obstacle Avoidance of**<br> **On Deep Reinforcement Learning**<br>
Xinyuan Wang\*<br> *Department of Transportation, Nanj* **and Intelligent Technology (SDIT2024)**<br> **Autonomous Navigation and Obstacle Avoidance**<br> **on Deep Reinforcement Learning**<br>
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\*Corres **Autonomous Navigation and Obstacle Avoidance of I<br>
on Deep Reinforcement Learning<br>
Xinyuan Wang\*<br>
Department of Transportation, Nanjing University of Aeronautics and Astronautic<br>
\*Corresponding author<br>
Abstract: This pape Autonomous Navigation and Obstacle Avoidance of 1**<br> **on Deep Reinforcement Learning**<br> *Ninyuan Wang\**<br> *Department of Transportation, Nanjing University of Aeronautics and Astronauti*<br>
\*Corresponding author<br> **Abstract:** T **limitations on Deep Reinforcement Learning**<br> **limitations of Transportation**, Nanjing University of Aeronautics and Astronaut<br>
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<b>autonomous navigatio Sunyuan Wang\***<br>
Department of Transportation, Nanjing University of Aeronautics and Astronaut<br>
\*Corresponding author<br> **Abstract:** This paper studies the developed within logistics<br>
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avoida **Learning Conversity of Aeronatius and Astronaution**<br> **learning** the the developed within logistics,<br> **autonomous navigation** and **obstacle** relief, and national<br> **avoidance technology of UAVs based on**<br> **learning analyz Performally and Corresponding aution**<br> **Perceive the surrounding autonomous** navigation and obstacle relief, and n<br>
avoidance technology of UAVs based on achieving self-a<br>
deep reinforcement learning, analyzes the avoidan Abstract: This paper studies the developed within logistics,<br>autonomous navigation and obstacle relief, and national c<br>avoidance technology of UAVs based on<br>deep reinforcement learning, analyzes the avoidance in UAVs still Abstract: This paper studies the developed within logistics<br>autonomous navigation and obstacle relief, and national<br>avoidance technology of UAVs based on<br>deep reinforcement learning, analyzes the avoidance in UAVs still fi Abstract: Ins paper studies the developed within<br>autonomous navigation and obstacle relief, and na<br>avoidance technology of UAVs based on achieving self-ac-<br>limitations of traditional navigation and especially with<br>obstacle **Example 10 increase the autonomous increase the autonomous increase the autoionious deep reinforcement learning, analyzes the avoidance in UAVs in the obstacle avoidance methods, and proposes a feature environment s Example 18 and 18** deep reinforcement tearning, analyzes the<br>
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dobstacle avoidance methods, and proposes a<br>
feature environments<br>
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<b>environments through deep reinforcement** environments and cannot<br> **larning.** Deep r **particular,** an in-depth analysis is<br> **particular, and complexe and stational entirement**<br> **entirements through deep reinforcement learning can**<br> **particular, and interpentival entirement**<br> **particular, and significantly conducted** the surviviron and algorithm perceive the surviviron and the survivironment the survivironment environment environment environment environment environment environment environment tend<br>**flight path in real time, convergence** the surrounding environment in the surrounding environment price the the surrounding environment that in environment equilibrium the medicine, and significantly mavigation and obstacles and significantly mavi perceive the surrounding environment<br>
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dynamic obstacles, and sign **algorithm in real time**, and state and state and potential in achieving efflight path and dynamic obstacles, and significantly navigation and obstacle a improve the autonomy and task execution through autonomously lear ef **ingnit pain in real time, avoid static and by the procedual in achievity<br>
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systematically explores the core concepts Traditional navigation<br>
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conducted on environmental maps, which convergence and stability of dynamic<br>
convergence and stability of dynamic<br>
obstacle avoidance, and optimization of<br>
algorithm performance of im Fortune of the stability of dynamic convergence and stability of dynamic obstacle avoidance, and optimization of reduce dependence algorithm performance, emphasizing the systems through many dimportance of improving the re **EXECUTE CONVERGINGLE AVOIDED**<br> **Algorithm performance, emphasizing the** systems through<br> **Algorithm in propertional continuous**<br> **Avoid and optimization** of reduce depende<br> **Avoid and propertional continuous**<br> **Avoid appl** Importance of Improving the real-<br>performance of the algorithm<br>autonomous flight of UAVs,<br>demonstrating the technical advantages<br>broad application prospects of<br>reinforcement learning in UAV naviga<br>tasks.<br>Keywords: UAV Navi

**Flight**

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Sending House**<br> **CE Avoidance of UAVs Based<br>
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developed within logistics, agriculture, disaster<br>
relief, and national defense. However,<br>
achieving self-acting navigat **next Learning**<br> **Solution**<br> **Aeronautics and Astronautics**, Nanjing, China<br> **Constant Complex Complex Assement Complex**<br> **Complex**<br> **Complex**<br> **Complex**<br> **Constant Complex**<br> **Constant Complex**<br> **Constant Constant Complex Example 18 Example 18 Astronautics**, Nanjing, China<br> *Astronautics* and Astronautics, Nanjing, China<br>
developed within logistics, agriculture, disaster<br>
relief, and national defense. However,<br>
achieving self-acting navig **Example 3**<br> **Aeronautics and Astronautics**, Nanjing, China<br> **author**<br> **developed within logistics, agriculture, disaster<br>
relief, and national defense. However,<br>
achieving self-acting navigation and obstacle<br>
avoidance in Example 18**<br> **Example 18 Example 18**<br> **Example 18**<br> **Example 20**<br> **Example 20**<br> **Example 18**<br> **Example 20**<br> **Example 20** *Aeronautics and Astronautics, Nanying, China*<br> *author*<br> *author*<br> *developed within logistics, agriculture, disaster<br>
relief, and national defense. However,<br>
achieving self-acting navigation and obstacle<br>
avoidance in UA* relation and model and model and model and the production and the production and the avoidance in UAVs still faces great challenges, especially within dynamic and complex feature environments. Conventional rule-based navig developed within logistics, agriculture, disaster<br>relief, and national defense. However,<br>achieving self-acting navigation and obstacle<br>avoidance in UAVs still faces great challenges,<br>especially within dynamic and complex<br>f developed within logistics, agriculture, disaster<br>relief, and national defense. However,<br>achieving self-acting navigation and obstacle<br>avoidance in UAVs still faces great challenges,<br>sepecially within dynamic and complex<br>f developed within logistics, agriculture, disaster<br>relief, and national defense. However,<br>achieving self-acting navigation and obstacle<br>avoidance in UAVs still faces great challenges,<br>especially within dynamic and complex<br>f reliet, and national detense. However,<br>achieving self-acting navigation and obstacle<br>avoidance in UAVs still faces great challenges,<br>especially within dynamic and complex<br>feature environments. Conventional rule-based<br>navig achieving selt-acting navigation and obstacle<br>avoidance in UAVs still faces great challenges,<br>especially within dynamic and complex<br>feature environments. Conventional rule-based<br>navigation and obstacle avoidance methods<br>us avoidance in UAVs still faces great challenges,<br>especially within dynamic and complex<br>feature environments. Conventional rule-based<br>navigation and obstacle avoidance methods<br>usually perform quite poorly in these<br>environmen especially within dynamic and complex<br>feature environments. Conventional rule-based<br>navigation and obstacle avoidance methods<br>usually perform quite poorly in these<br>environments and cannot cope with the<br>unpredictability and feature environments. Conventional rule-based<br>navigation and obstacle avoidance methods<br>usually perform quite poorly in these<br>environments and cannot cope with the<br>unpredictability and complexity of such an<br>environment [1] navigation and obstacle avoidance methods<br>usually perform quite poorly in these<br>environments and cannot cope with the<br>unpredictability and complexity of such an<br>environment [1]. As a frontier in artificial<br>intelligence, DR

**1.1 Research Background and Importance**<br> **1.1 Research Packground Scription Scription** is exampled to the example the technical advantages and realized. For<br> **1.1 Research Background and Importance**<br> **1.1 Research Backgro** demonstrating the technical advantages and<br>
broad application prospects of deep<br>
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challenge Frame Teams and New Yorking in UAV and the probability content than the exceptionally cap<br>
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Reinforcement Learning; Obstacle DRL in UAVs<br>
Avoidance; Path Planning; Autono usually perform quite poorly in these<br>environments and cannot cope with the<br>unpredictability and complexity of such an<br>environment [1]. As a frontier in artificial<br>intelligence, DRL has recently shown great<br>potential in ac environments and cannot cope with the<br>unpredictability and complexity of such an<br>environment [1]. As a frontier in artificial<br>intelligence, DRL has recently shown great<br>potential in achieving efficient autonomous<br>navigatio unpredictability and complexity of such an<br>environment [1]. As a frontier in artificial<br>intelligence, DRL has recently shown great<br>potential in achieving efficient autonomous<br>navigation and obstacle avoidance for UAVs<br>thro environment [1]. As a frontier in artificial<br>intelligence, DRL has recently shown great<br>potential in achieving efficient autonomous<br>navigation and obstacle avoidance for UAVs<br>through autonomously learning and optimizing<br>st intelligence, DRL has recently shown great<br>potential in achieving efficient autonomous<br>navigation and obstacle avoidance for UAVs<br>through autonomously learning and optimizing<br>strategies [2].<br>Traditional navigation solution potential in achieving efficient autonomous<br>navigation and obstacle avoidance for UAVs<br>through autonomously learning and optimizing<br>strategies [2].<br>Traditional navigation solutions, including<br>simultaneous localization and navigation and obstacle avoidance for UAVs<br>through autonomously learning and optimizing<br>strategies [2].<br>Traditional navigation solutions, including<br>simultaneous localization and mapping<br>algorithms, all depend on high-preci through autonomously learning and optimizing<br>strategies [2].<br>Traditional navigation solutions, including<br>simultaneous localization and mapping<br>algorithms, all depend on high-precision<br>sensors and a large amount of computin strategies [2].<br>Traditional navigation solutions, including<br>simultaneous localization and mapping<br>algorithms, all depend on high-precision<br>sensors and a large amount of computing<br>resources to realize real-time updating of<br> Traditional navigation solutions, including<br>simultaneous localization and mapping<br>algorithms, all depend on high-precision<br>sensors and a large amount of computing<br>resources to realize real-time updating of<br>environmental ma simultaneous localization and mapping<br>algorithms, all depend on high-precision<br>sensors and a large amount of computing<br>resources to realize real-time updating of<br>environmental maps, which is greatly limited<br>in practical us algorithms, all depend on high-precision<br>sensors and a large amount of computing<br>resources to realize real-time updating of<br>environmental maps, which is greatly limited<br>in practical use [3]. On the contrary, DRL may<br>reduce sensors and a large amount of computing<br>resources to realize real-time updating of<br>environmental maps, which is greatly limited<br>in practical use [3]. On the contrary, DRL may<br>reduce dependence on sophisticated sensor<br>syste resources to realize real-time updating of<br>environmental maps, which is greatly limited<br>in practical use [3]. On the contrary, DRL may<br>reduce dependence on sophisticated sensor<br>systems through mapping the sensor data of<br>UA environmental maps, which is greatly limited<br>in practical use [3]. On the contrary, DRL may<br>reduce dependence on sophisticated sensor<br>systems through mapping the sensor data of<br>UAVs into control signals directly and thus<br>h In practical use [3]. On the contrary, DRL may<br>reduce dependence on sophisticated sensor<br>systems through mapping the sensor data of<br>UAVs into control signals directly and thus<br>have the independent navigation and obstacle<br> reduce dependence on sophisticated sensor<br>systems through mapping the sensor data of<br>UAVs into control signals directly and thus<br>have the independent navigation and obstacle<br>avoidance of complex three-dimensional space<br>rea systems through mapping the sensor data of<br>UAVs into control signals directly and thus<br>have the independent navigation and obstacle<br>avoidance of complex three-dimensional space<br>realized. For this unique solution to the<br>pro UAVs into control signals directly and thus<br>have the independent navigation and obstacle<br>avoidance of complex three-dimensional space<br>realized. For this unique solution to the<br>problem of independent navigation and<br>obstacle have the independent navigation and obstacle<br>avoidance of complex three-dimensional space<br>realized. For this unique solution to the<br>problem of independent navigation and<br>obstacle avoidance of UAVs, DRL is<br>exceptionally cap avoidance of complex three-dimensional space<br>realized. For this unique solution to the<br>problem of independent navigation and<br>obstacle avoidance of UAVs, DRL is<br>exceptionally capable of conquering the<br>challenge brought by a realized. For this unique solution to the<br>problem of independent navigation and<br>obstacle avoidance of UAVs, DRL is<br>exceptionally capable of conquering the<br>challenge brought by a complex and dynamic<br>environment. The success problem of independent navigation and<br>obstacle avoidance of UAVs, DRL is<br>exceptionally capable of conquering the<br>challenge brought by a complex and dynamic<br>environment. The successful application of<br>DRL in UAVs not only pr obstacle avoidance of UAVs, DRL is<br>exceptionally capable of conquering the<br>challenge brought by a complex and dynamic<br>environment. The successful application of<br>DRL in UAVs not only promotes the<br>development of automation t



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This study aims to explore the application of<br>
deep reinforcement learning in drone** 

**1.2 Academic Education**<br> **1.2 Research Objectives**<br> **1.3 Re** The method of the application<br>
Conference on Section<br>
academically valuable and have a wide range<br>
of applications [5].<br>
1.2 Research Objectives<br>
This study aims to explore the application of<br>
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1.2 Research Objectives<br>
This study aims t **Examplement Education**<br> **Environmental Properties**<br> **Examplement Tech**<br>
academically valuable and have a wide range<br>
algorithms like SLAM,<br>
of applications [5].<br>
1.2 Research Objectives<br>
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of applications [5].<br> **1.2 Research Objectives** and have a wide range algorithms like SLAN<br>
mavigate t The state of applications [5].<br>
academically valuable and have a wide range algorithms like S<br>
of applications [5].<br>
While these technology;<br>
This study aims to explore the application of a device limitations<br>
deep reinfor academically valuable and have a wide range<br>
of applications [5].<br>
1.2 Research Objectives<br>
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This study aims to explore the application of<br>
device limitations, especies<br>
deep r of applications [5]. The avigate through unit of the set chinology<br>
1.2 Research Objectives<br>
This study aims to explore the application of a device limitations, esteep reinforcement learning in drone device limitations, an 1.2 Research Objectives<br>
This study aims to explore the application of<br>
deep reinforcement learning in drone<br>
autonomous navigation and obstacle avoidance,<br>
and propose a drone navigation and obstacle<br>
avoidance strategy t 1.2 Research Objectives are also high com<br>
This study aims to explore the application of alevice limitations<br>
deep reinforcement learning in drone real-time process<br>
autonomous navigation and obstacle avoidance,<br>
avoidance This study aims to explore the application of<br>
deep reinforcement learning in drone<br>
arothomomus navigation and obstacle<br>
and propose a drone navigation and obstacle<br>
avoidance strategy that can adapt to complex<br>
environm deep reinforcement learning in drone real-time processing<br>autonomous navigation and obstacle avoidance,<br>avoidance strategy that can adapt to complex<br>avoidance<br>environments. Specifically, this study will<br>**Obstacle Avoidance** autonomous navigation and obstacle avoidance,<br>
and propose a drone navigation and obstacle<br>
avoidance strategy that can adapt to complex<br>
avoidance strategy that can adapt to complex<br>
environments. Specifically, this study and propose a drone navigation and obstacle<br>avoidance strategy that can adapt to complex<br>environments. Specifically, this study will<br>solve the following key problems: first, how to Obstacle avoidance Techn<br>improve the path avoidance strategy that can adapt to complex<br>
environments. Specifically, this study will<br>
obstacle Avoidance Te<br>
solve the following key problems: first, how to Obstacle avoidance tecl<br>
improve the path planning ability o environments. Specifically, this study will<br>solve the following key problems: first, how to<br>disolve the path planning ability of drones<br>through environmental perception technology;<br>of UAVs, which<br>second, how to ensure the solve the tollowing key problems: first, how to Costacle avoidance technol<br>improve the path planning ability of drones<br>the composition technologies in the auto-<br>through environmental perception technology; second, how to e mprove the path planning ability of drones<br>
second, how to ensue the convergence and<br>
stability of deep reinforcement learning<br>
approaches and<br>
algorithms in dynamic obstacle environments;<br>
and finally, how to optimize the through environmental perception technology; of UAVs, wi<br>second, how to ensure the convergence and categories: in<br>stability of deep reinforcement learning approaches a<br>algorithms in dynamic obstacle environments; avoidance Example to the provides and finally, how to optimize the performance and of deep reinforcement learning algorithms to solidance meth obstacle avoidance and finally, how to optimize the performance of deep reinforcement lea algorithms in dynamic obstacle environments;<br>
and finally, how to optimize the performance<br>
of deep reinforcement learning algorithms to<br>
improve their efficiency in real-time<br>
information from the pure<br>
navigation tasks. mprove their enticlency in real-time<br>
navigation tasks. This study will not only and thus avoiding observe<br>
verify the effectiveness of the algorithm<br>
through simulation, but also explore the future<br>
development direction mavigation tasks. This study will not only<br>verify the effectiveness of the algorithm<br>through simulation, but also explore the future<br>development direction of deep reinforcement<br>learning in drone navigation, aiming to<br>provi verify the effectiveness of the algorithm<br>through simulation, but also explore the future method is fast and<br>development direction of deep reinforcement limited computing<br>learning in drone navigation, aiming to dynamic env

# **Technology**

Example a new technical path for the intelligent<br>
and automated development of drones.<br>
1 and automated development of drones.<br>
1 and automated development of drones.<br>
2. **Current Status of Drone Autonomous**<br>
1 Obstacle av provide a new technical path for the intelligent<br>
and automated development of drones.<br> **2. Current Status of Drone Autonomous**<br> **Navigation and Obstacle Avoidance** based on the chinology<br> **2.1 Traditional Methods of Drone** and automated development of drones.<br>
2. **Current Status of Drone Autonomous**<br> **Cobstacle avoidance**<br> **Cobstacle avoidance**<br> **Cobstacle avoidance**<br> **Cobstacle avoidance**<br> **Cobstacle avoidance**<br> **Cobstacle avoidance**<br> **Cobs** 2. Current Status of Drone Autonomous<br>
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technologies sucl<br>
2.1 Traditional Methods of Drone global path-plan<br> 2. Current Status of Drone Autonomous<br>
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Technology<br>
Traditional Methods of Drone<br>
technologies such as SI<br>
Autonomous Navigation<br>
In the early days, drone autonomous<br>
Autonomous Navigatio Navigation and Obstacle Avoidance planning a safe path in the dechologies such as<br>
technology<br>
2.1 Traditional Methods of Drone technology<br>
Autonomous Navigation<br>
In the early days, drone autonomous the purpose of na<br>
mavi Technology<br>
2.1 Traditional Methods of Drone<br>
Autonomous Navigation<br>
Autonomous Navigation<br>
In the early days, drone autonomous<br>
In the early days, drone autonomous<br>
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algorithm, for instance 2.1 Traditional Methods of Drone technologies such as SL<br>
Autonomous Navigation<br>
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mavigation technology mainly depends on<br>
some traditional navigation algorithms and<br>
some traditional na 2.1 Traditional Methods of Drone global path-planning alge<br>
Autonomous Navigation<br>
In the early days, drone autonomous<br>
mavigation technology mainly depends on<br>
avoidance [11]. Such an ap<br>
some traditional navigation algo **Autonomous Navigation**<br>
In the early days, drone autonomous<br>
navigation dechnology mainly depends on<br>
some traditional navigation algorithms and<br>
some traditional navigation algorithms and<br>
more optimized obstacle a<br>
sens In the early days, drone autonomous the purpose of navigation argume traditional navigation algorithms and some traditional arises the model sensor technologies. One of the classic complex environments, but methods represe navigation technology manily depends on avoidance [11]. Si<br>some traditional navigation algorithms and more optimized c<br>sensor technologies. One of the classic complex environm<br>methods represents navigation based on GPS com some traditional navigation algorithms and<br>
sensor technologies. One of the classic<br>
methods represents navigation based on GPS<br>
and INS. These approaches provide very<br>
and INS. These approaches provide very<br>
accurate posi sensor technologies. One of the classic complex environments, but<br>methods represents navigation based on GPS computational cost. The up<br>accurate positioning and heading information<br>devices the colume-sepecially applied in methods represents navigation based on GPS<br>
and INS. These approaches provide very<br>
accurate positioning and heading information<br>
by fusing GPS signals and IMU data, and are<br>
long comput<br>
widely applied in UAV navigation i and INS. These approaches provide very<br>accurate positioning and heading information<br>three-dimensional environment with the widely applied in UAV navigation in outdoor<br>open space [6]. However, GPS navigation in a learning h accurate positioning and heading information<br>we fusing GPS signals and IMU data, and are<br>widely applied in UAV navigation in outdoor<br>were proper space [6]. However, GPS navigation in a<br>clemning has received much<br>complex en by fusing GPS signals and IMU data, and are<br>
widely applied in UAV navigation in outdoor<br>
open space [6]. However, GPS navigation in a<br>
complex environment with features such as an<br>
due to the devel<br>
urban canyon, forest,

### **International Conference on Social Development and Intelligent Technology (SDIT2024)**

**Academic Education**<br> **Academic Education**<br> **Academically valuable and have a wide range**<br> **Academically valuable and have a wide range**<br> **Academically valuable and have a wide range**<br> **Academically valuable and have a wid Trational Conference on Social Development**<br> **and Intelligent Technology (SDIT2024)**<br>
algorithms like SLAM, enabling UAVs to<br>
navigate through unknown environments.<br>
While these technologies are in wide use, there<br>
are al rnational Conference on Social Development<br>
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are also high computing costs and hardware<br>
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algorithms like SLAM, enabling UAVs to<br>
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While these technologies are in wide use, there<br>
are als **and Intelligent Technology (SDIT2024)**<br>algorithms like SLAM, enabling UAVs to<br>navigate through unknown environments.<br>While these technologies are in wide use, there<br>are also high computing costs and hardware<br>device limita

algorithms like SLAM, enabling UAVs to<br>algorithms like SLAM, enabling UAVs to<br>avigate through unknown environments.<br>While these technologies are in wide use, there<br>are also high computing costs and hardware<br>device limitati algorithms like SLAM, enabling UAVs to<br>navigate through unknown environments.<br>While these technologies are in wide use, there<br>are also high computing costs and hardware<br>device limitations, especially in the need for<br>real-t may the through unknown environments.<br>
While these technologies are in wide use, there<br>
are also high computing costs and hardware<br>
device limitations, especially in the need for<br>
real-time processing of massive amounts of While these technologies are in wide use, there<br>are also high computing costs and hardware<br>device limitations, especially in the need for<br>real-time processing of massive amounts of<br>data to ensure flying safety for UAVs [8] are also high computing costs and hardware<br>device limitations, especially in the need for<br>real-time processing of massive amounts of<br>data to ensure flying safety for UAVs [8].<br>2.2 Classification and Comparison of<br>Obstacle device limitations, especially in the need for<br>real-time processing of massive amounts of<br>data to ensure flying safety for UAVs [8].<br>2.2 Classification and Comparison of<br>Obstacle Avoidance Technologies<br>Obstacle avoidance t real-time processing of massive amounts of<br>data to ensure flying safety for UAVs [8].<br>2.2 Classification and Comparison of<br>Obstacle Avoidance Technologies<br>Obstacle avoidance technology is one of the<br>key technologies in the data to ensure flying safety for UAVs [8].<br>
2.2 Classification and Comparison of<br>
Obstacle Avoidance Technologies<br>
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key technologies in the autonomous navigation<br>
of UAVs, which 2.2 Classification and Comparison of<br>
Obstacle Avoidance Technologies<br>
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key technologies in the autonomous navigation<br>
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categories: reactiv 2.2 Classification and Comparison of<br>
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Obstacle avoidance technologies<br>
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Obstacle avoidance technology is one of the<br>
key technologies in the autonomous navigation<br>
of UAVs, which can be divided into two<br>
categories: reactive obstacle avoidance<br>
approaches an Obstacle avoidance technology is one of the<br>key technologies in the autonomous navigation<br>of UAVs, which can be divided into two<br>categories: reactive obstacle avoidance<br>approaches and planning-based obstacle<br>avoidance meth key technologies in the autonomous navigation<br>of UAVs, which can be divided into two<br>categories: reactive obstacle avoidance<br>approaches and planning-based obstacle<br>avoidance methods. Normally, the reactive<br>obstacle avoidan of UAVs, which can be divided into two<br>categories: reactive obstacle avoidance<br>approaches and planning-based obstacle<br>avoidance methods. Normally, the reactive<br>obstacle avoidance methods would utilize<br>sensors for the purpo categories: reactive obstacle avoidance<br>approaches and planning-based obstacle<br>avoidance methods. Normally, the reactive<br>obstacle avoidance methods would utilize<br>sensors for the purpose of acquiring real-time<br>information f approaches and planning-based obstacle<br>avoidance methods. Normally, the reactive<br>obstacle avoidance methods would utilize<br>sensors for the purpose of acquiring real-time<br>information from the surrounding environment<br>and thus avoidance methods. Normally, the reactive<br>obstacle avoidance methods would utilize<br>sensors for the purpose of acquiring real-time<br>information from the surrounding environment<br>and thus avoiding obstacles simply based on<br>cer obstacle avoidance methods would utilize<br>sensors for the purpose of acquiring real-time<br>information from the surrounding environment<br>and thus avoiding obstacles simply based on<br>certain rule or strategy [9]. This kind of<br>m sensors for the purpose of acquiring real-time<br>information from the surrounding environment<br>and thus avoiding obstacles simply based on<br>certain rule or strategy [9]. This kind of<br>method is fast and suitable for scenarios

through simulation, but also explore the future<br>
development direction of deep reinforcement<br>
limited computing resource<br>
lemaring in drome navigation, aiming to<br>
provide a new technical path for the intelligent<br>
and autom development direction of deep reinforcement<br>
learning in drone navigation, aiming to<br>
provide a new technical path for the intelligent<br>
and automated development of drones.<br> **2. Current Status of Drone Autonomous**<br> **2. Cur** information from the surrounding environment<br>and thus avoiding obstacles simply based on<br>certain rule or strategy [9]. This kind of<br>method is fast and suitable for scenarios with<br>limited computing resources. But in a compl and thus avoiding obstacles simply based on<br>certain rule or strategy [9]. This kind of<br>method is fast and suitable for scenarios with<br>limited computing resources. But in a complex<br>dynamic environment, its performance is ve certain rule or strategy [9]. This kind of<br>method is fast and suitable for scenarios with<br>limited computing resources. But in a complex<br>dynamic environment, its performance is very<br>poor and it cannot predict the movement<br> method is fast and suitable for scenarios with<br>limited computing resources. But in a complex<br>dynamic environment, its performance is very<br>poor and it cannot predict the movement<br>trajectory of obstacles effectively [10].<br>Ob limited computing resources. But in a complex<br>dynamic environment, its performance is very<br>poor and it cannot predict the movement<br>trajectory of obstacles effectively [10].<br>Obstacle avoidance with path planning, on the<br>oth dynamic environment, its performance is very<br>poor and it cannot predict the movement<br>trajectory of obstacles effectively [10].<br>Obstacle avoidance with path planning, on the<br>other hand, avoids an obstacle by first<br>planning poor and it cannot predict the movement<br>trajectory of obstacles effectively [10].<br>Obstacle avoidance with path planning, on the<br>other hand, avoids an obstacle by first<br>planning a safe path in advance. This class of<br>methods trajectory of obstacles effectively [10].<br>
Obstacle avoidance with path planning, on the<br>
other hand, avoids an obstacle by first<br>
planning a safe path in advance. This class of<br>
methods usually depends on map building<br>
te Obstacle avoidance with path planning, on the<br>other hand, avoids an obstacle by first<br>planning a safe path in advance. This class of<br>methods usually depends on map building<br>technologies such as SLAM and couples<br>global pat other hand, avoids an obstacle by first<br>planning a safe path in advance. This class of<br>methods usually depends on map building<br>technologies such as SLAM and couples<br>global path-planning algorithms (Dijkstra's<br>algorithm, fo planning a sate path in advance. This class of<br>methods usually depends on map building<br>technologies such as SLAM and couples<br>global path-planning algorithms (Dijkstra's<br>algorithm, for instance, or A\* algorithm) for<br>the pur methods usually depends on map building<br>technologies such as SLAM and couples<br>global path-planning algorithms (Dijkstra's<br>algorithm, for instance, or A\* algorithm) for<br>the purpose of navigation and obstacle<br>avoidance [11]. technologies such as SLAM and couples<br>global path-planning algorithms (Dijkstra's<br>algorithm, for instance, or A\* algorithm) for<br>the purpose of navigation and obstacle<br>avoidance [11]. Such an approach may design<br>more optimi global path-planning algorithms (Dijkstra's<br>algorithm, for instance, or A\* algorithm) for<br>the purpose of navigation and obstacle<br>avoidance [11]. Such an approach may design<br>more optimized obstacle avoidance routes in<br>compl algorithm, for instance, or A\* algorithm) for<br>the purpose of navigation and obstacle<br>avoidance [11]. Such an approach may design<br>more optimized obstacle avoidance routes in<br>complex environments, but it is at a very high<br>co the purpose of navigation and obstacle<br>avoidance [11]. Such an approach may design<br>more optimized obstacle avoidance routes in<br>complex environments, but it is at a very high<br>computational cost. The updating of maps in<br>real avoidance [11]. Such an approach may design<br>more optimized obstacle avoidance routes in<br>complex environments, but it is at a very high<br>computational cost. The updating of maps in<br>real time-especially in large-scale<br>three-d more optimized obstacle avoidance routes in<br>complex environments, but it is at a very high<br>computational cost. The updating of maps in<br>real time-especially in large-scale<br>three-dimensional environments-can result in<br>long c computational cost. The updating of maps in<br>real time-especially in large-scale<br>three-dimensional environments-can result in<br>long computational delays. Obstacle avoidance<br>technology based on deep reinforcement<br>learning has three-dimensional environments-can result in<br>long computational delays. Obstacle avoidance<br>technology based on deep reinforcement<br>learning has received much attention recently<br>due to the development of deep learning<br>techno long computational delays. Obstacle avoidance<br>technology based on deep reinforcement<br>learning has received much attention recently<br>due to the development of deep learning<br>technology. Such technology has prominent<br>advantage

# **Technologies**

### **International Conference on Social Development and Intelligent Technology (SDIT2024)**

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and Intelligent Technology (SDIT2024)<br>
there are still so many limitations. Firstly,<br>
navigation and obstacle avoidance<br>
technologies based on traditional sensors an immediat **International Conference on Social Development**<br> **and Intelligent Technology (SDIT2024)**<br>
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navigation and obstacle avoidance<br>
technologies based on traditional sensors an imm **International Conference on Social Development**<br> **and Intelligent Technology (SDIT2024)**<br>
there are still so many limitations. Firstly,<br>
transition probability<br>
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there are still so many limitations. Firstly,<br>
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there are still so many limitations. Firstly,<br>
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there are still so many limitations. Firstly,<br>
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there are still so many limitations. Firstly,<br>
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technologies based on traditional sensors and im **and Intelligent Technology (SDIT2024)**<br>
there are still so many limitations. Firstly,<br>
navigation and obstacle avoidance<br>
technologies based on traditional sensors an immediate reward<br>
perform very poor, including in com and interaction and obstacles methods based an immediate reward  $r_i = R$ <br>navigation and obstacle avoidance technologies based on traditional sensors an immediate reward  $r_i = R$ <br>perform very poor, including in computing the a there are still so many limitations. Firstly, transition probability  $P(\text{envologies based on traditional sensors})$  an immediate reward  $r_i$  is<br>perform very poor, including in computing the agent is to find the op<br>resources and energy consumption, espe mavigation and obstacle avoidance<br>technologies based on traditional sensors<br>perform very poor, including in computing<br>resources and energy consumption, especially maximize the cumula<br>when flying drones are limited in size technologies based on traditional sensors and immediate countar<br>perform very poor, including in computing the agent is to find the op<br>resources and energy consumption, especially when flying drones are limited in size and perform very poor, including in computing<br>
resources and energy consumption, especially<br>
when flying drones are limited in size and<br>
weight and hardly portable with<br>
high-performance sensors [13]. Delays in<br>
real-time pla resources and energy consumption, especially maximize the cumula<br>
when flying drones are limited in size and  $G_t$ :<br>
wigh-performance sensors [13]. Delays in<br>
real-time planning due to high-velocity flying<br>
could result in when flying drones are limited in size and<br>
weight and hardly portable with<br>
high-performance sensors [13]. Delays in<br>
real-time planning due to high-velocity flying<br>
could result in collision-risk conditions.<br>
Second, mo weight and hardly portable with<br>
high-performance sensors [13]. Delays in<br>
real-time planing due to high-velocity flying<br>
could result in collision-risk conditions.  $Q(s, a_i) = r_i + \gamma \max_{a_{i\alpha}} Q(s_i, a_i)$ <br>
Second, most current obs high-performance sensors [13]. Delays in  $G_t = \sum_{k=1}^{\infty}$ <br>
real-time planning due to high-velocity flying<br>
could result in collision-risk conditions. Second, most current obstacle avoidance<br>
methods lack the ability to h real-time planning due to high-velocity flying<br>
could result in collision-risk conditions.<br>
Second, most current obstacle avoidance<br>
methods lack the ability to handle dynamic used to balance<br>
obstacles. Third, for traini could result in collision-risk conditions.<br>
Second, most current obstacle avoidance<br>
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environment with complex conditi Second, most current obstacle avoidance<br>
methods lack the ability to handle dynamic<br>
obstacles. Third, for training in an<br>
environment with complex conditions, most<br>
environment learning obstacle<br>
environment learning obs methods lack the ability to handle dynamic<br>
obstacles. Third, for training in an long-term benefits. The<br>
environment with complex conditions, most<br>
environment canning obstacle<br>
avoidance methods require large<br>
actor-cri obstacles. Third, for training in an environment with complex conditions, most<br>deep reinforcement learning obstacle<br>avoidance methods require large<br>computational resources and time, and learned<br>policies cannot be quickly a **EXEMPLE THE SET APPLICATE ASSAGE THE CONSUMATE CONSUMATE CONSUMATE CONDUST**<br> **3. Overview and Application of Deep**<br> **3. Overview and Algorithms of Deep**<br> **3. Approximate FR**<br> **3. Approximate Set Approximate Set Approxima** avoidance methods require large<br>
computational resources and time, and learned<br>
policies cannot be quickly adapted to changes<br>
in the environment for real-time applications<br>
[14]. The other serious challenge is related to<br> poincies cannot be quickly adapted to changes<br>
in the environment for real-time applications<br>
[14]. The other serious challenge is related to<br>
the lack of current environmental perception<br>
along with navigation stability, in the environment for real-time applications<br>
[14]. The other serious challenge is related to<br>
the lack of current environmental perception<br>
along with navigation stability, especially<br>
when the drones have to fly for an [14]. The other serious challenge is related to<br>the lack of current environmental perception<br>the ack of current environmental perception<br>when the drones have to fly for an extended<br>duration in the three-dimensional comple the lack of current environmental perception<br>
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when the drones have to fly for an extended<br>
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duration in the three-dimensional complex<br>
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along with navigation stability, especially<br>
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enough [15].<br> **3. Overview and Application of Deep**<br> **3. Overview and Application of Deep**<br> duration in the three-dimensional complex<br>
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Reinforcement Learning<br>
3.1 Basic Concepts and Algorithms of environment; a system cannot be robust<br>
enough [15].<br> **3. Overview and Application of Deep**<br> **Reinforcement Learning**<br> **3.1 Basic Concepts and Algorithms of Deep**<br>
This formula indicates<br> **Reinforcement Learning**<br>
Deep re enough [15].<br> **S. Overview and Application of Deep**<br>
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Deep reinforcement learni 3. Overview and Application of Deep<br>
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2.1 Basic Concepts and Algorithms of Deep<br>
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Deep reinforcement learning<br>
Deep reinforcement learni **3. Overview and Application of Deep** gradient is:<br> **Reinforcement Learning**  $\nabla_{\theta}J(\theta) = \Phi_{\pi_{\theta}}[\nabla_{\theta} \log \pi_{\theta}(a)]$ <br> **a Basic Concepts and Algorithms of Deep** This formula indicates<br> **Reinforcement Learning** (DRL) is **Reinforcement Learning**<br> **and Algorithms of Deep**<br> **Reinforcement Learning**<br>
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Deep reinforcement learning (DRL) is a<br>
bechnology that combines reinforcement<br>
learning and deep learning, aiming to solve<br>
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Deep reinforcement learning (DRL) is a<br>
technology that combines reinforcement<br>
learning and deep learning, aiming to solve<br>
tasks with high-dimensional input space and<br>
tasks with high-dimensiona Deep remforcement learning (DRL) is<br>technology that combines reinforcement<br>learning and deep learning, aiming to solv<br>tasks with high-dimensional input space an<br>complex decision-making processes. The cor<br>idea of reinforcem technology that combines reinforcement<br>
learning and deep learning, aiming to solve<br>
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the best learning and deep learning, aiming to solve<br>
tasks with high-dimensional input space and<br>
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dea of reinforcement learning is to learn<br>
the best strategy to maximize the cumulativ tasks with high-dimensional input space and<br>
complex decision-making processes. The core<br>
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the best strategy to maximize the cumulative<br>
are **Obstacle Avoidance**<br>
the complex decision-making processes. The core<br>
idea of reinforcement learning is to learn<br>
the best strategy to maximize the cumulative<br>
reward through the interaction between the used in autonomous<br>
agent and the environme idea of reinforcement learning is to learn<br>
the best strategy to maximize the cumulative Deep reinfor<br>
reward through the interaction between the<br>
and error process. DRL uses deep neural<br>
and aror process. DRL uses deep n learning and deep learning, aiming to solve<br>tasks with high-dimensional input space and<br>complex decision-making processes. The ore<br>diea of reinforcement learning is to learn<br>the best strategy to maximize the cumulative<br>th

agent and the environment in a continuous trial<br>and error process. DRL uses deep neural<br>networks to represent the policy function or<br>avoid static or dynamic<br>value function, enabling it to process complex<br>places high deman



transition probability  $P(s_{i+1} | s_i, a_i)$ , and obtains<br>an immediate reward  $r_i = R(s_i, a_i)$ . The goal of<br>the agent is to find the optimal strategy  $\pi^*$  to<br>maximize the cumulative discounted reward  $G_i$ . **An Academic Education**<br>
transition probability  $P(s_{i+1} | s_i, a_i)$ , and obtains<br>
an immediate reward  $r_i = R(s_i, a_i)$ . The goal of<br>
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maximize the cumulative discounted reward<br> The Education<br>
Ing House<br>
, and obtains<br>
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rategy  $\pi^*$  to<br>
unted reward **the agent is to find the controller in the controller of the agent is to find the optimal strategy**  $\pi^*$  **to maximize the cumulative discounted reward**  $G_t$ **:<br>**  $G = \sum_{k=1}^{\infty} \gamma^k r$  **(1)** the agent is to find the optimal strategy  $\pi^*$  to to **Constraint (The Control Archatter Controller Controller School Controller (The cumulative discounted reward**  $r_i = R(s_i, a_i)$ **)** The goal of the agent is to find the optimal strategy  $\pi^*$  to maximize the cumulative discounte  $G_t$ . **depending House**<br> **c f** *t e t***<sub>shm</sub> <b>***t t c <i>t c t t c t c t c t c t c t c t c t c t c t c t c t* **Containing House**<br> **G** *F* **Containing House**<br> **Containing Pointing House**<br> **Contained**  $r_i = R(s_i, a_i)$ , and obtains<br>
to find the optimal strategy  $\pi^*$  to<br>
to example the control of example  $\pi^*$  to<br>  $G_t = \sum_{k=0}^{\infty}$ **Constraint Container Controlling Controlling Controlling Constant**<br>transition probability  $P(s_{t+1} | s_t, a_t)$ , and obtains<br>an immediate reward  $r_t = R(s_t, a_t)$ . The goal of<br>the agent is to find the optimal strategy  $\pi^*$  to<br>ma **1 C**<br> **1 Academic Education**<br> **tion probability**  $P(s_{t+1} | s_t, a_t)$ , and obtains<br>
mediate reward  $r_t = R(s_t, a_t)$ . The goal of<br>
gent is to find the optimal strategy  $\pi^*$  to<br>
mize the cumulative discounted reward<br>  $G_t = \sum_{k=0}^{\infty} \gamma^k$ **Anomia Education**<br> **Anomia Education**<br> **Contains**<br> **Contains**<br>

$$
G_{t} = \sum_{k=0}^{\infty} \gamma^{k} r_{t+k+1}
$$
 (1)

$$
Q(s_t, a_t) = r_t + \gamma \max_{a_{t+1}} Q(s_{t+1}, a_{t+1})
$$
\n(2)

**Publishing House**<br>
transition probability  $P(s_{t+1} | s_t, a_t)$ , and obtains<br>
an immediate reward  $r_i = R(s_t, a_t)$ . The goal of<br>
the agent is to find the optimal strategy  $\pi^*$  to<br>
maximize the cumulative discounted reward<br>  $G_t$ transition probability  $P(s_{t+1} | s_t, a_t)$ , and obtains<br>an immediate reward  $r_i = R(s_t, a_t)$ . The goal of<br>the agent is to find the optimal strategy  $\pi^*$  to<br>maximize the cumulative discounted reward<br> $G_t$ :<br> $G_t = \sum_{k=0}^{\infty} \gamma^k r_{$ transition probability  ${}^{F(S_{i+1} S_i, a_i)}$ , and obtains<br>an immediate reward  $r_i = R(s_i, a_i)$ . The goal of<br>the agent is to find the optimal strategy  $\pi^*$  to<br>maximize the cumulative discounted reward<br> $G_i$ :<br> $G_i = \sum_{k=0}^{\infty} \gamma^k r$ an immediate reward  $r_i = R(s_i, a_i)$ . The goal of<br>the agent is to find the optimal strategy  $\pi^*$  to<br>maximize the cumulative discounted reward<br> $G_t$ :<br> $G_t = \sum_{k=0}^{\infty} \gamma^k r_{t+k+1}$  (1)<br> $Q(s_i, a_i) = r_i + \gamma \max_{a_{i=1}} Q(s_{t+1}, a_{t+1})$  (2)<br> the agent is to find the optimal strategy  $\pi^*$  to<br>maximize the cumulative discounted reward<br> $G_t$ :<br> $G_t = \sum_{k=0}^{\infty} \gamma^k r_{t+k+1}$  (1)<br> $Q(s_t, a_t) = r_t + \gamma \max_{a_{t+1}} Q(s_{t+1}, a_{t+1})$  (2)<br>Among them,  $\gamma \in [0,1]$  is a discount factor<br>u transition probability  $P(s_{i+1} | s_i, a_i)$ , and obtains<br>an immediate reward  $r_i = R(s_i, a_i)$ . The goal of<br>the agent is to find the optimal strategy  $\pi^*$  to<br>maximize the cumulative discounted reward<br> $G_i$ :<br> $G_i = \sum_{k=0}^{\infty} \gamma^k r_{$  $G_t$ :<br>  $G_t = \sum_{k=0}^{\infty} \gamma^k r_{t+k+1}$  (1)<br>  $Q(s_t, a_t) = r_t + \gamma \max_{a_{t+1}} Q(s_{t+1}, a_{t+1})$  (2)<br>
Among them,  $\gamma \in [0,1]$  is a discount factor<br>
used to balance short-term rewards and<br>
long-term benefits. The key algorithms of deep<br>
rei an immediate reward  $r_i = R(s_i, a_i)$ . The goal of<br>the agent is to find the optimal strategy  $\pi^*$  to<br>maximize the cumulative discounted reward<br> $G_i$ :<br> $G_i = \sum_{k=0}^{\infty} \gamma^k r_{i+k+1}$  (1)<br> $Q(s_i, a_i) = r_i + \gamma \max_{a_{i+1}} Q(s_{i+1}, a_{i+1})$  (2)<br>  $G_t = \sum_{k=0} Y^k r_{t+k+1}$  (1)<br>  $Q(s_t, a_t) = r_t + \gamma \max_{a_{t+1}} Q(s_{t+1}, a_{t+1})$  (2)<br>
Among them,  $Y \in [0,1]$  is a discount factor<br>
used to balance short-term rewards and<br>
long-term benefits. The key algorithms of deep<br>
reinforcement lea  $Q(s_i, a_i) = r_i + \gamma \max_{a_{i+1}} Q(s_{i+1}, a_{i+1})$  (2)<br>Among them,  $\gamma \in [0,1]$  is a discount factor<br>used to balance short-term rewards and<br>long-term benefits. The key algorithms of deep<br>reinforcement learning include deep Q<br>network (D  $Q(s_i, a_i) = r_i + \gamma \max_{a_{i+1}} Q(s_{i+1}, a_{i+1})$  (2)<br>Among them,  $\gamma \in [0,1]$  is a discount factor<br>used to balance short-term rewards and<br>long-term benefits. The key algorithms of deep<br>reinforcement learning include deep Q<br>network (D  $G_i = \sum_{k=0}^{\infty} \gamma^k r_{i+k+1}$  (1)<br>  $Q(s_i, a_i) = r_i + \gamma \max_{a_{i+1}} Q(s_{i+1}, a_{i+1})$  (2)<br>
Among them,  $\gamma \in [0,1]$  is a discount factor<br>
aused to balance short-term rewards and<br>
long-term benefits. The key algorithms of deep<br>
reinforce used to balance short-term rewards and<br>long-term benefits. The key algorithms of deep<br>reinforcement learning include deep Q<br>network (DQN), policy gradient method and<br>actor-critic method. In DQN, the Q value<br>function  $Q(s,a)$ long-term benefits. The key algorithms of deep<br>reinforcement learning include deep Q<br>network (DQN), policy gradient method and<br>actor-critic method. In DQN, the Q value<br>function  $Q(s,a)$  represents the expected<br>cumulative re reinforcement learning include deep Q<br>network (DQN), policy gradient method and<br>actor-critic method. In DQN, the Q value<br>function  $Q(s,a)$  represents the expected<br>cumulative reward after selecting action <sup>a</sup> in<br>state <sup>S</sup>. A network (DQN), policy gradient method and<br>actor-critic method. In DQN, the Q value<br>function  $Q(s,a)$  represents the expected<br>cumulative reward after selecting action  $a$  in<br>state  $S$ . Approximate  $Q(s,a)$  through a deep<br>neura to balance short-term rewards and<br> *Jerm* benefits. The key algorithms of deep<br>
ccement learning include deep Q<br> *Z*(DQN), policy gradient method and<br> *Jritic* method. In DQN, the Q value<br>
on  $Q(s,a)$  represents the expecte ong them,  $\gamma \in [0,1]$  is a discount factor<br>
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forcement learning include deep Q<br>
orork (DQN), policy gradient method and<br>
r-critic method. In

function  $e^{(s,w)}$  represents the expected<br>cumulative reward after selecting action  $a$  in<br>state  $S$ . Approximate  $Q(s,a)$  through a deep<br>neural network, and continuously update the Q<br>value through the Bellman equation<br>In ad cumulative reward arter selecting action " in<br>state S. Approximate  $Q(s,a)$  through a deep<br>neural network, and continuously update the Q<br>value through the Bellman equation<br>In addition, the policy gradient method<br>directly op state <sup>5</sup>. Approximate  $\mathcal{Q}^{(s,a)}$  through a deep<br>neural network, and continuously update the Q<br>value through the Bellman equation<br>In addition, the policy gradient method<br>directly optimizes the policy  $\pi(a|s)$  by<br>perfor actor-critic method. In DQIN, the Q value<br>function  $Q(s,a)$  represents the expected<br>cumulative reward after selecting action <sup>a</sup> in<br>state *S*. Approximate  $Q(s,a)$  through a deep<br>neural network, and continuously update the Q<br> In addition, the policy gradient inethod<br>directly optimizes the policy  $\pi(a|s)$  by<br>performing gradient ascent on the policy<br>parameters  $\theta$  to maximize the cumulative<br>reward. The update formula of the policy<br>gradient is:<br> directly optimizes the policy  $A(u, s)$  by<br>performing gradient ascent on the policy<br>parameters  $\theta$  to maximize the cumulative<br>reward. The update formula of the policy<br>gradient is:<br> $\nabla_{\theta}J(\theta) = \tilde{\sigma}_{\pi_{\theta}} [\nabla_{\theta} \log \pi_{\theta}(a$ 

$$
\nabla_{\theta} J(\theta) = \bar{\mathbf{a}}_{\pi_{\theta}} \left[ \nabla_{\theta} \log \pi_{\theta}(a \,|\, s) Q^{\pi}(s, a) \right] \tag{3}
$$

performing gradient ascent on the policy<br>parameters  $\theta$  to maximize the cumulative<br>reward. The update formula of the policy<br>gradient is:<br> $\nabla_{\theta}J(\theta) = \bar{\sigma}_{\pi_{\theta}} [\nabla_{\theta} \log \pi_{\theta}(a|s)Q^{\pi}(s,a)]$  (3)<br>This formula indicates th

The set of the same that the same that the set of drones are allowed in autonomous trial<br>time in a avoidance of drones. Drep neural autonomously in complex<br>images or somplex places high demands<br>images or robustness and co ep learning, aiming to solve<br>
-d-mensional input space and<br>
-n-making processes. The core<br> **Reinforcement Learning in Nav**<br>
forcement learning is to learn<br>  $\sigma$  **to** maximize the cumulative<br>  $\sigma$  **to** maximize the cumulat attive<br>
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autonomously in complex<br>
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algorithms often parameters  $\theta$  to maximize the cumulative<br>reward. The update formula of the policy<br>gradient is:<br> $\nabla_{\theta}J(\theta) = \bar{\mathfrak{a}}_{\pi_{\theta}} [\nabla_{\theta} \log \pi_{\theta}(a|s)Q^{\pi}(s,a)]$  (3)<br>This formula indicates that the policy is<br>updated based on th reward. The update formula of the policy<br>gradient is:<br> $\nabla_{\theta}J(\theta) = \bar{\mathfrak{a}}_{\pi_{\theta}} [\nabla_{\theta} \log \pi_{\theta}(a | s)Q^{\pi}(s, a)]$  (3)<br>This formula indicates that the policy is<br>updated based on the parameter gradient of the<br>policy  $\pi$  by gradient is:<br>  $\nabla_{\theta}J(\theta) = \bar{\sigma}_{\pi_{\theta}} \left[ \nabla_{\theta} \log \pi_{\theta}(a|s) Q^{\pi}(s,a) \right]$  (3)<br>
This formula indicates that the policy is<br>
updated based on the parameter gradient of the<br>
policy  $\pi$  by sampling experience to<br>
maximize the  $\nabla_{\theta}J(\theta) = \vec{\sigma}_{\pi_{\theta}} \left[ \nabla_{\theta} \log \pi_{\theta}(a|s) Q^{\pi}(s,a) \right]$  (3)<br>
This formula indicates that the policy is<br>
updated based on the parameter gradient of the<br>
policy  $\pi$  by sampling experience to<br>
maximize the performance o This formula indicates that the policy is<br>updated based on the parameter gradient of the<br>policy  $\pi$  by sampling experience to<br>maximize the performance of the policy  $J(\theta)$ .<br>3.2 Analysis of the Application of Deep<br>Reinfor This formula indicates that the policy is<br>updated based on the parameter gradient of the<br>policy  $\pi$  by sampling experience to<br>maximize the performance of the policy  $J(\theta)$ .<br>3.2 Analysis of the Application of Deep<br>Reinfor dependent of the parameter gradient of the<br>policy  $\pi$  by sampling experience to<br>maximize the performance of the policy  $J(\theta)$ .<br>3.2 Analysis of the Application of Deep<br>Reinforcement Learning in Navigation and<br>Obstacle Avo policy and by sampling experience to<br>maximize the performance of the policy  $J(\theta)$ .<br>3.2 Analysis of the Application of Deep<br>Reinforcement Learning in Navigation and<br>Obstacle Avoidance<br>Deep reinforcement learning is increa maximize the performance of the policy  $\sigma(\nu)$ .<br>
3.2 Analysis of the Application of Deep<br>
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used in autonomous navig 3.2 Analysis of the Application of Deep<br>Reinforcement Learning in Navigation and<br>Obstacle Avoidance<br>Deep reinforcement learning is increasingly<br>used in autonomous navigation and obstacle<br>avoidance of drones. Drones need to 3.2 Analysis of the Application of Deep<br>
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Deep reinforcement learning is increasingly<br>
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Deep reinforcement learning is increasingly<br>
used in autonomous navigation and obstacle<br>
avoidance of drones. Drones need to navigate<br>
autonomously in complex environments and<br>
avoid static or dynamic Deep reinforcement learning is increasingly<br>used in autonomous navigation and obstacle<br>avoidance of drones. Drones need to navigate<br>autonomously in complex environments and<br>avoid static or dynamic obstacles, which<br>places h used in autonomous navigation and obstacl<br>avoidance of drones. Drones need to navigat<br>autonomously in complex environments an<br>avoid static or dynamic obstacles, whic<br>places high demands on the real-tim<br>robustness and compu avoidance of drones. Drones need to navigate<br>autonomously in complex environments and<br>avoid static or dynamic obstacles, which<br>places high demands on the real-time,<br>robustness and computing performance of the<br>algorithm. Tr

**Andemic Education**<br> **Andemic Education**<br> **Andemic Education**<br> **Andemic Education**<br> **Andemic Publishing House**<br> **Andemic Publishing House**<br> **Andemic Publishing House**<br> **Andemic Publishing House**<br> **Andemic Publishing a**<br> **A COM**<br> **Example Education**<br> **Exam COMORET CONTROVIDE CONTROVIDED ACCORDING THE PUBLISHING PUBLISHING PUBLISHING PUBLISHING AND AN END AND AN ENTIRE SURVEY THE AND AN END AND THE SURVEY CONDUCT AN EXAMPLE THE AND ANY LOT AND ANY LOT AND AN EXAMPLE ONLY LAT Academic Education**<br> **Academic Education**<br> **Academic Education**<br> **Academic Education**<br> **Academic environment to avoid collisions and<br>
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minimize flight time. In an e Figure 1 shows the application<br>
Figure 1 shows the autonomously adjust its flight path in a [12]. The simulation env<br>
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minimize flight time. In an environment with<br>
dynamic obsta **From Conferential Conferential Conferential Conferential Conferential Conferential Conferential autonomously adjust its flight path in a [12]. The simulat dynamic environment to avoid collisions and trains an agent (u min Example 18**<br> **Example 28** 

# **International Conference on Social Development and Intelligent Technology (SDIT2024)**

**Example 12**<br> **Example 12 Trains and Intelligent Technology (SDIT2024)**<br>
[12]. The simulation environment on the left<br>
trains an agent (using a deep neural network)<br>
to perform navigation tasks in a simulated<br>
environment. The agent adjusts its st **Transional Conference on Social Development**<br> **and Intelligent Technology (SDIT2024)**<br>
[12]. The simulation environment on the left<br>
trains an agent (using a deep neural network)<br>
to perform navigation tasks in a simulate **rnational Conference on Social Development**<br> **and Intelligent Technology (SDIT2024)**<br>
[12]. The simulation environment on the left<br>
trains an agent (using a deep neural network)<br>
to perform navigation tasks in a simulated **rnational Conference on Social Development**<br> **and Intelligent Technology (SDIT2024)**<br>
[12]. The simulation environment on the left<br>
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to perform navigation tasks in a simulated rnational Conference on Social Development<br>and Intelligent Technology (SDIT2024)<br>[12]. The simulation environment on the left<br>trains an agent (using a deep neural network)<br>to perform navigation tasks in a simulated<br>environ rnational Conference on Social Development<br>and Intelligent Technology (SDIT2024)<br>[12]. The simulation environment on the left<br>trains an agent (using a deep neural network)<br>to perform navigation tasks in a simulated<br>environ rnational Conference on Social Development<br>
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[12]. The simulation environment on the left<br>
trains an agent (using a deep neural network)<br>
to perform navigation tasks in a simulated<br>
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# **Navigation**

# **Planning**

Figure 1. Application Process of Deep Reinforcement Learning in Autom<br>
Obstacle Avoidance of Drones<br>
Dynamic obstacle average of Deep<br>
A. Key Issues and Challenges of Deep<br>
Reinforcement Learning for Drone by task in auton Figure 1. Application Process of Deep Reinforcement Learning in<br>
Mostacle Avoidance of Drones<br>
A. Key Issues and Challenges of Deep<br>
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Reinforcement Learning for Drone<br>
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1.1 Environmental Perception and Path<br>
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planning are the k 4.1 Environmental Perception and Path<br>
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planning are the key to achieving accurate<br>
algorithms often cannot<br>
na In the process of autonomous navigation of<br>
drones, environmental perception and path<br>
palaming are the key to achieving accurate<br>
navigation and safe flight. Environmental resulting in navigation<br>
perception relies on the drones, environmental perception and path<br>
palanning are the key to achieving accurate<br>
navigation and safe flight. Environmental<br>
perception relies on the drone's sensors, such<br>
perception relies on the drone's sensors, w planning are the key to achieving accurate algorithms often cannot the avoigation relation endics on the drone's sensors, such incinicorement learning as lidar, canneras, or ultrasonic sensors, which dynamic changes by car mavigation and sate thight. Environmental<br>perception relies on the drone's sensors, such<br>as ident, cameras, or ultrasonic sensors, which<br>are used to detect surrounding obstacles and<br>are used to detect surrounding obstacles perception relies on the drone's sensors, such<br>as lidar, cameras, or ultrasonic sensors, which dynamic chang<br>are used to detect surrounding obstacles and strategies, but s<br>path features. However, sensor data is usually str as lidar, cameras, or ultrasonic sensors, which<br>
are used to detect surrounding obstacles and<br>
particular strategies, but slow<br>
uncertain or noisy, and how to deal with these<br>
deviations during trip<br>
imprecise data is a ch and the surrounding obstacles and strategies, but slow conver<br>
path features. However, sensor data is usually<br>
increation or noisy, and how to deal with these<br>
imprecise data is a challenge. At the same time, the rapid con path teatures. However, sensor data is usually strategies matues interest in or noisy, and how to deal with these deviations due imprecise data is a challenge. At the same time, the rapid codep reinforcement learning needs mprecise data is a challenge. At the same time,<br>
deep reinforcement learning needs to use these<br>
perception information for path planning to<br>
ensure that the drone can find the optimal path<br>
in a complex environment. In a<br> deep reinforcement learning needs to use these<br>perception information for path planning to<br>ensure that the drone can find the optimal path<br>in a complex environment. In a<br>high-dimensional continuous state space, path<br>planni

Figure 1. Application Process of Deep Reinforcement Learning in Autonomous<br>
Agent/deep neural network<br>
Desired policy<br>
Assemble Avoidance of Drones<br>
Dynamic obstacle avoidance<br>
A. Key Issues and Challenges of Deep<br>
Reinfor Figure 1. Application Process of Deep Reinforcement Learning in Autonomous<br>
Obstacle Avoidance of Drones<br>
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A. Key Issues and Challenges of Deep<br>
Reinforcement Learning for Drone<br>
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Dynamic obstacle avoidance is an important<br>
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Dynamic obstacle avoidance is an important<br>
task in autonomous navigation of drones,<br>
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content **Learning in Autonomous Navigation and**<br> **cof Drones**<br>
Dynamic obstacle avoidance is an important<br>
task in autonomous navigation of drones,<br>
especially when there are moving obstacles in<br>
th **Example 19016)**<br> **Example 10 Connect Connect Connect Connect Connect Connect Connect Connect task in autonomous navigation of drones, especially when there are moving obstacles in the environment. A major challenge of d** From the and the seat of the seat of the strategies and the strategies and the strategies are different task in autonomous navigation of drones, especially when there are moving obstacles in the environment. A major challe **reflexaming in Autonomous Navigation and**<br> **e of Drones**<br>
Dynamic obstacle avoidance is an important<br>
task in autonomous navigation of drones,<br>
especially when there are moving obstacles in<br>
the environment. A major chall **Dynamic obstacle avoidance is an important**<br>
task in autonomous navigation of drones,<br>
especially when there are moving obstacles in<br>
the environment. A major challenge of deep<br>
reinforcement learning in this case is how Dynamic obstacle avoidance is an important<br>task in autonomous navigation of drones,<br>especially when there are moving obstacles in<br>the environment. A major challenge of deep<br>reinforcement learning in this case is how to<br>ens task in autonomous navigation of drones,<br>especially when there are moving obstacles in<br>the environment. A major challenge of deep<br>reinforcement learning in this case is how to<br>ensure that the algorithm converges to a stabl especially when there are moving obstacles in<br>the environment. A major challenge of deep<br>reinforcement learning in this case is how to<br>ensure that the algorithm converges to a stable<br>strategy in a dynamic environment. Beca the environment. A major challenge of deep<br>reinforcement learning in this case is how to<br>ensure that the algorithm converges to a stable<br>strategy in a dynamic environment. Because<br>the position and speed of obstacles are<br>co remforcement learning in this case is how to<br>ensure that the algorithm converges to a stable<br>strategy in a dynamic environment. Because<br>the position and speed of obstacles are<br>constantly changing, traditional path planning ensure that the algorithm converges to a stable<br>strategy in a dynamic environment. Because<br>the position and speed of obstacles are<br>constantly changing, traditional path planning<br>algorithms often cannot be updated in time,<br> strategy in a dynamic environment. Because<br>the position and speed of obstacles are<br>constantly changing, traditional path planning<br>algorithms often cannot be updated in time,<br>resulting in navigation failure. Deep<br>reinforcem the position and speed of obstacles are<br>constantly changing, traditional path planning<br>algorithms often cannot be updated in time,<br>resulting in navigation failure. Deep<br>reinforcement learning copes with these<br>dynamic chang algorithms often cannot be updated in time,<br>resulting in navigation failure. Deep<br>reinforcement learning copes with these<br>dynamic changes by constantly adjusting<br>strategies, but slow convergence or unstable<br>strategies may resulting in navigation railine. Deep<br>reinforcement learning copes with these<br>dynamic changes by constantly adjusting<br>strategies, but slow convergence or unstable<br>strategies may lead to collisions or path<br>deviations during reinforcement learning copes with these<br>dynamic changes by constantly adjusting<br>strategies, but slow convergence or unstable<br>strategies may lead to collisions or path<br>deviations during training. Therefore, ensuring<br>the rap dynamic changes by constantly adjusting<br>strategies, but slow convergence or unstable<br>strategies may lead to collisions or path<br>deviations during training. Therefore, ensuring<br>the rapid convergence and stability of the<br>algo strategies, but slow convergence or unstable<br>strategies may lead to collisions or path<br>deviations during training. Therefore, ensuring<br>the rapid convergence and stability of the<br>algorithm in a dynamic environment is an<br>imp

strategies may lead to collisions or path<br>deviations during training. Therefore, ensuring<br>the rapid convergence and stability of the<br>algorithm in a dynamic environment is an<br>important issue for UAV navigation, which<br>requir deviations during training. Therefore, ensuring<br>the rapid convergence and stability of the<br>algorithm in a dynamic environment is an<br>important issue for UAV navigation, which<br>requires more efficient exploration strategies<br>a the rapid convergence and stability of the<br>algorithm in a dynamic environment is an<br>important issue for UAV navigation, which<br>requires more efficient exploration strategies<br>and more accurate value function estimation.<br>4.3 algorithm in a dynamic environment is an important issue for UAV navigation, which requires more efficient exploration strategies and more accurate value function estimation.<br>
4.3 Algorithm Performance Optimization and Rea

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