Multi-Agent Reinforcement Learning-Based Evacuation Models under Emergency

FINAL REPORT

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16. Abstract

Reinforcement learning (RL) has been widely used in intelligent transportation systems, especially under emergent situations, RL can explore the dangerous environment and make optimal decisions to guide the evacuation process for human beings. Within RL algorithms, a Multi-agent Reinforcement Learning (MARL) an artificial intelligence-based model that enables multiple agents to communicate and respond to emergent situations for a more efficient exploration and evacuation process, especially when the uncertainty level is high. This study simulated robot agents to explore and evacuate from a dynamic environment with or without collaboration using the MARL Q-learning algorithm. The multi-agent collaboration method was found to perform better than the single-agent exploration regarding the evacuation time, death counts, and reward both in the static threats and dynamic threats environment. Results were discussed, and future directions were given in the end.

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Executive Summary

With the considerable development of the air transportation system in recent years, the demand for a more efficient evacuation system for airport security services has been increased. The purpose of the study is to investigate the utilization of different machine learning methods using Reinforcement Learning (RL) to optimize evacuation in dynamic and complex environments such as fire, terrorist attacks and more, particularly in an environment such as airport. RL has been widely used in intelligent transportation systems, especially under emergent situations, and can explore the dangerous environment and make optimal decisions to guide the evacuation process for human beings. Within RL algorithms, a Multi-agent Reinforcement Learning (MARL) is an artificial intelligence-based model that enables multiple agents to communicate and respond to emergent situations for a more efficient exploration and evacuation process, especially when the uncertainty level is high. This study simulated robot agents to explore and evacuate from a dynamic environment with or without collaboration using the MARL Q-learning algorithm. The multi-agent collaboration method was found to perform better than the single-agent exploration regarding the evacuation time, death counts, and reward both in the static threats and dynamic threats environment. Results were discussed, and future directions were given in the end.

Introduction

Background

In the past decades, the air transportation industry has been expanding rapidly along with the flourishing trajectory of the global economy (Airport Emergency Plan, 2011). The evolution of modern aviation has raised the demand for airport security services and the necessity for more efficient evacuation strategies in the emergencies such as natural disaster like fire or terrorist attack.

An emergency usually occurs instantaneously, requiring immediate decision-making ability (Wang et al., 2016). It is especially the case true for the environments like airports. According to Title 14 Code of Federal Regulations (CFR), Part 139, airport certificate holders must develop and maintain an Airport Emergency Plan (AEP) to minimize the damage, whether to human or property in an emergency, as a part of their airport certification manual (Airport Emergency Plan, 2011). More detailed suggestions are given by the Federal Aviation Administration (FAA) in the Advisory Circulars (AC) 150/5200-31C (FAA, 2009). Therefore, it is imperative to continue pushing the technological capabilities and improve current emergency evacuation strategies.

The Current State of Evacuation Plans

The current emergency drill models use the existing case studies and expriments to prevent future accidents, which can be inefficient and resource-consuming (Arumugam et al., 2016). However, evacuation plans simulated through “mock drills” sometimes cannot truly simulate the real situations thus are not able to react to sudden hazards in

time effectively. For instance, airport fire evacuation drills cannot simulate the situation of falling objects blocking the exits on the evacuation routes. In reality, when similar unexpected scenarios occur, the crowd is likely to panic, people at the scene are prone to cause crowd trampling, stampede, which might result in loss of life (Balachandar et al., 2019). Thus, a method that can intelligently generate evacuation routes according to the discrepancies in each specific emergency circumstance can be lifesaving.

Conventional approaches to generating an evacuation path plan concentrate on computer modeling techniques (Bi et al., 2019; Bunea et al., 2016). Computer simulation technology protects volunteers' safety, which may occur dangerous in “mock drills” in reality and provides valuable evacuation information (Carino & Garciano, 2019). The modeling methods, such as the social force model (SFM) (FAA, 2009) and the hybrid model (Feng & Wang, 2019), are based on creating fundamental rules to control each agent's movement. It is prone to ignore the interaction with other agents and the environment.

Like many public transportation environments, airports are rather complex environments that comprise numerous social interactions (Gelada & Buckman, 2019). Therefore, for traditional non-learning-based algorithms, simulating the entire airport environment and generating evacuation routes for each agent is relatively time-consuming and often far from optimal.

Agent-Based Learning

The hazardous environments with unidentified threats expose first responders and evacuees to significant risks. Robot agents or drones exploring the dangerous

environment before the human evacuation can decrease the risk for the people involved. With the assistance of robot agents or drones, the evacuees can find the optimal evacuation routes without wandering around in distress situations and exposed to unknown dangers. While the agents were exploring the environment, the updated routes can be shown to human evacuees as a digital decision aid on devices such as mobile apps. The real-time revised map becomes more straightforward as the agent learns more about the changing circumstances. First responders and evacuees can add holistic views and their relative locations to facilitate the evacuation process. On the other hand, robot agents can be integrated into the AEP or other emergency procedures to improve efficiency in dealing with emergencies planning and policy making.

Emergencies are unpredictable, and people need to be evacuated from dangerous places to secure shelters as soon as possible. Researchers from different disciplines have discovered different paths to enhance the efficiency of emergency evacuations, and they have provided valuable suggestions (Arumugam et al., 2016; Bunea et al., 2016; Liu et al., 2016; Makinoshima et al., 2016; Shen et al., 2015; Wang et al., 2016). More and more researchers in this field, as of late, have shown interest in agent-based modeling for emergency evacuation, especially for complex scenarios that can transpire in unsecure environments.

Within these simulation models, reinforcement Learning (RL) has become more popular in evacuation primarily among all the machine-learning models because of its capability of "learning through exploration." The agent learns through trial-and-error while interacting with the environment that helps it make the right decision (Bunea et al., 2016). RL does not require specific control over the environment or models about the

environment but instead uses positive and negative rewards to determine the best future decision. This feature is critical for emergencies, as the threats and environments are usually unidentified to decision-makers, without explicit solutions for such evacuation tasks. RL also allows agents to learn from themselves and others through the rewards and punishment mechanism, making RL an ideal method for exploring and learning an unknown environment with unknown threats.

In improving evacuation efficiency, learning-based RL variation algorithms have drawn interest from many researchers. In a large-scale and convoluted environment, multi-agent reinforcement learning (MARL) can be applied (Isele et al., 2018) to allow agents to interact with the dynamic environment and perceive it through reward and punishment signals to maximize the reward by trial and error. MARL is considered the closest algorithm related to the knowledge accumulation path taken by humans in reality (de Witt et al., 2018). Some researchers have already adapted those characteristics to the path planning problem (Xu et al., 2020; Fatima et al., 2017). However, the adaption of MARL to the airport evacuation simulation is not straightforward. That is part of the reason that this study was intended to present a systematic study including environment simulation, model design, and analysis of evacuation behavior in macro and micro ways. Macroscopically speaking, the agents can learn the optimal evacuation path universally. The agents can avoid dynamic obstacles and correct the route according to the challenges that block the original course in the micro aspect. Agent rewards, success rate, and evacuation time were used to evaluate the learning efficiency.

Furthermore, this study also compared the performance of single-agent exploration and multi-agent collaboration during emergency evacuation using RL

algorithms. Two different environments were utilized in the study: the simple environment with one threat and the complex environment with three threats. The benefits of MARL was further verified using a more dynamic and realistic airport diagram.

It is believed that agent-based modeling effectively simulates emergency evacuation as the agent represents the actual human/robot that makes stochastic decisions and movements. The overall rational for using multiple agents is that a single robot agent is usually used to explore different environments, but it can take a long time to learn and complete the exploration. Multiple agents exploring can lessen the time consumed, especially when agents communicate and collaborate.

Summary

In this study we intended to investigate the difference in the performance between single-agent exploration and multi-agent exploration regarding time, death counts, and rewards. The interaction between the complexity of the environment and the numbers agents were also investigated.

To summarize, the main contributions of this study are as follows:

1. Complex environments were used to simulate the airport like situations. Not only static obstacles were used to train the model, but this paper also simulated the situation that the obstacles could move randomly or move in a specified trajectory.
2. Agents' communications were investigated in the study. This paper takes a new sharing Q-table mechanism to enhance the learning convergence rate among

agents. Multi-agents share their Q-table as a “communication” mechanism. At each step, agents update their own Q-table and record their update value on the summary table. Then agents take actions that will get the most reward based on the summary table. In this way, the success rate, evacuation time, and convergence rate will be improved effectively. As a result, this method is more suitable for solving the evacuation problems.

Review of the Relevant Literature

Evacuation Safety

Emergency evacuation is a complex and dangerous situation where critical decisions must be made under extreme time pressures (Wang et al., 2016), and lives could be saved if correct decisions were made promptly. During an emergency, the public may not be able to make the optimal decisions with limited time and information due to the complex nature of the emergency situation. Furthermore, an emergency can often cause chaos and congestion, especially in public transportation where the pedestrian density is high (Feng & Wang, 2019). The efficiency and safety of the emergency evacuation would be greatly compromised if proper training or assistance was not provided before or during the emergency evacuation (Purser, 2015).

For example, in an investigation of two care-home fires, evacuees were unable to identify the fire location and nearby doors due to training inadequacies. Several lives were lost in minutes because of the poor evacuation response and strategy (Purser, 2015). It may seem intuitive to find the optimal evacuation route based on the memory and prior experience, but the situation is quite different under emergency evacuation. People may panic, and under the high time pressure, they could lose the ability to think rationally and make reasonable decisions. Researchers have found several ways to improve this situation by advance assessment and evacuation assistance (Cariño & Garciano, 2019; Zhang et al., 2016; Yamamoto et al., 2018; Zhang & Yi, 2015). A little help during the evacuation may seem negligible, but the help may allow the time for thinking and offer a way to survive.

Many models were developed to assess the risk under the emergency. For example, Zhang et al. (2016) proposed a steel-temperature rise model to assess the risk of evacuation safety in the collapse of a large steel-structured building. This model can be used to make emergency plans for steel-structured buildings when encountering disasters like earthquakes. It can also be used to improve people's awareness of safe evacuation routes during a crisis. Cariño and Garciano (2019) developed a seismic evacuation safety index to help assess evacuation safety for schools. The evacuation safety index can help schools to evaluate the safety of the classroom and campus building to ensure the solidity of the structure during the evacuation.

There are also various models developed to investigate different evacuation situations, such as evacuation from buildings and classrooms, tsunami evacuation, toxic environment evacuation, and post-disaster evacuation (Liu et al., 2016; Wang et al., 2016). Modeling specific types of emergencies can help people better understand the nature of the events, what to expect, and how to react. Detailed emergency evacuation plans can thus be designed to accommodate different facilities layouts and for different purposes.

Liu et al. (2016) simulated a classroom evacuation situation to investigate how evacuation efficiency is affected by classroom layouts. The classroom with more exits had a significantly higher efficiency in the evacuation, and students who followed the guidance could evacuate faster and safer. During the evacuation, teachers may lose control of the situation which makes the training for teachers and students essential. It is suggested for school officials to conduct more fire drills regularly. Students can learn to evacuate safely and efficiently through frequent drills and avoid dangerous and chaotic

evacuations in real emergency situations, as in the fatal care home fires (Purser, 2015). Liu et al. (2016) also suggested that future studies should look into specific type of emergencies, such as a bombing or earthquake, as students may show different responses for different situations. For the same reason, different emergency plans are needed for different types of situations.

On a larger scale, Wang et al. (2016) simulated a multimodal near-field tsunami evacuation. The near-field tsunamis represent the middle range of five hazard groups (Earthquake, building fire, tsunami, wildfire, and hurricane). For the middle range hazard group, there are usually 20 to 40 minutes warnings window before the actual disaster hits, so the quicker and better the decision is made, the more lives can be saved. In the simulation, evacuees had options of whether to hide in the shelter or evacuate by car in the near-field tsunami evacuation model. Each option had its pros and cons regarding the safety and efficiency of this evacuation, and evacuees cannot simply tell which mode of transportation is better. It is a complex evacuation simulation involving more than just making a simple choice (Wang et al., 2016). Wang et al (2016) investigated the effect of different individual decision-making time scales to assess the mortality rate due to immediate evacuation right after an initial earthquake or after a specified milling time. Simulation of the evacuation showed some unexpected results which gave people more insights into the emergency evacuation.

The results from the study above gave people some insight about evacuation safety during near-field tsunamis. First of all, there is a strong correlation between the individual decision time and the mortality rate of the disaster, and the faster people make the right response, the more likely that they will survive which makes sense as they have

more time to evacuate. Secondly, different structures have different resistance to the disaster, and vertical evacuation structures were more helpful than other structures, so the structure of the escape route and the shelter must be evaluated from time to time. Furthermore, depending on the actual emergency, the model for moving pedestrians should be changed accordingly. As in the emergency evacuation of the tsunami, the more people used the car, the fewer people could survive as the tsunami moves fast while people are congested on the road (Wang et al., 2016).

In addition to these results, it is advised to include partial damage to the transportation network as it is commonly seen during catastrophic events. The vulnerability of the facility, congestion on the road, and accessibility and user-friendliness of public transportation all need to be considered to better identify the bottleneck effects in the evacuation simulation models for future studies. Makinoshima et al. (2016) also presented an evacuation simulation model based on the evacuation behaviors observed during the Great East Japan Earthquake and Tsunami. Makinoshima et al. (2016) compiled the data from previous studies, surveys, and reports and developed an evacuation simulation model. In the evacuation model developed from the historical data, main roads were used for evacuation, and shelter preferences and pedestrian-car interactions were also considered. By doing so, this model was able to better estimate the actual evacuation behaviors during the catastrophic event.

For the post-disaster simulation, Bunea et al. (2016) modeled how individuals react after the disaster. Their study analyzed the scenario in the city of Iaşi, Romania. Iaşi has a high seismic vulnerability as it has a lot of old buildings. Bunea et al. (2016)

simulated an evacuation situation for the earthquake as people need to cross three bridges before entering the hospitals or shelters.

In their study, the time taken for evacuees to move across the three bridges was recorded. The vulnerability and damage of the earthquake to the bridges were taken into consideration, and different degrees of damage was included in the simulation to replicate the actual situation (Bunea et al., 2016). Their study built a good basis for a further experiment on evacuation safety in areas with many old buildings. The time for people to cross the bridge and enter the shelter can be further related to the mortality rate to show the feasibility of the structure of the city as the research done by Wang et al. (2016).

Besides the assessment of the situation before emergency, the real-time support and assistance during the disaster is also critical for the safety and efficiency of the evacuees during the evacuation. For assistance during the evacuation, Yamamoto et al. (2018) used numerical simulation to understand the effects of the new ventilation equipment on the tunnel fire. For the tunnel fire, the use of the new ventilation equipment can improve the environment greatly and make it much easier for evacuees to escape.

The Application of ML and RL in Evacuation

Machine learning is different from human learning in terms of the way systems learn. One advantage of using machine learning in evacuation is that it can protect humans from exploring dangerous situations. If the machine can learn to find the exit during the evacuation, the danger can be transferred to the machine such as drones or robot agents instead of human pedestrians.

Machine learning is based on the concept that systems learn from the dataset, identify the pattern, and make decisions. There are mainly three types of machine learning including supervised learning, unsupervised learning, and reinforcement learning.

Supervised learning is to learn how to map from the attributes describing an instance to the targeted attribute, i.e., learning from a labeled dataset with guidance (Kelleher & Tierney, 2018). Unsupervised learning is to learn without a targeted attribute, i.e., learning from an unlabeled dataset without guidance. Without the targeted attribute, unsupervised learning becomes more difficult as the task becomes more general, such as looking for the regularities in the dataset (Kelleher & Tierney, 2018). Reinforcement learning (RL) is a branch of machine learning area based on the concept that systems learn from the dataset, identify the pattern, and make decisions. The learning-based algorithm could make the computer learn itself by exploration and exploitation (Ferber et al., 2004), primarily for the reinforcement learning algorithm.

Reinforcement Learning

Reinforcement learning encourages the agents to obtain the most rewards in the circumstances through the interaction between the agent and the environment. The algorithm is informed when the agents' behavior is incorrect, but the proper behavior response is not disclosed. Unlike supervised learning, agents are not granted explicit inputs and outputs. Because of these features, reinforcement learning has been widely applied in numerous fields of study (Lovas, 1998), with strong online learning and self-learning capabilities in complex environments. However, reinforcement learning has

relatively poor convergence ability than other machine learning algorithms (Weiss & Ed, 1999). Designing the reward function and optimization function so that reinforcement learning can converge quickly in a complex environment is the key to the proper application of reinforcement learning in actual scenarios.

The fundamental reinforcement learning algorithm is based on the Markov decision processes (MDPs), which are a classical formalization of sequential decision making, where the existing action will not only influence the immediate rewards, but also long-term returns (Zhou et al., 2017). MDPs regularize the reinforcement learning by the sequence of,

$$M = (S, A, P, R, \gamma)$$

The sequence comprises a set of states, S, actions A, transition probability P, reward value from the current environment R, and the discount factor γ. Specifically, according to the distribution of time steps, MDPs have two categories: the continuous domain and the discrete domain Markov decision-making process. The agents plan to discover the best optimization decision and get the best cumulative reward R in the current environment, which can be addressed as an MDPs problem.

Reinforcement learning based on Markov decisions can be divided into two categories, namely model-based dynamic programming learning and model-free learning. Gelada and Buckman (2019) demonstrated that model-based and model-free learning are equivalent in sampling efficiency. In contrast, the difference between the two algorithms lies in the balance between understanding the dynamic characteristics of the agent or forcing the best policy in the actual application scenario. Model-based reinforcement learning is mainly divided into value-based learning such as Q series learning (Le et al.,

2017; Liu et al., 2016) and State-Action-Reward-State-Action (Sarsa), and policy-based learning such as Actor-Critic. In short, RL is quite different from the other machine learning methods because it learns by interacting with the environment without any prior datasets. An RL agent makes the most efficient decision at a given state by trial-and-error, and the only input is delayed scalar reward (Tan, 1993). For this reason, RL is extremely beneficial for evacuation simulation with unknown threats as there is no dataset provided during evacuation process.

RL has been applied in a wide range of evacuation situations. For example, researchers have used RL to adapt the complex agent-based model to a fast-linear model to solve the optimization of guidance sign for tsunami evacuation (Le et al., 2017), model situations such as sensor sensitivity of autonomous aerial vehicles (Quirion et al., 2014; Quirion et al., 2015), and get the optimal route recommendations during the emergency evacuations (Bi et al., 2019).

Yao et al. (2019) proposed a data-driven cloud evacuation framework based on RL. This cloud evacuation framework can simulate human behaviors even when the environment is changing. The model established by Yao et al. (2019) extracted position and velocity information from videos of real-life evacuations and then used a cloud simulation system to generate the results. The evacuation model can improve efficiency and safety greatly in advance which can be applied in real-life situations.

To give some other examples, Piyabhum et al. (2020) and Tian et al. (2018) proposed a suitable state space and reward function which results in an efficient collaborative double Q-learning RL algorithm. Arai et al. (2000) and Busoniu et al. (2005) introduce the cut-loop routine in reinforcement learning that discards looping

behavior and demonstrate its effectiveness empirically within a simplified NEO (non-combatant evacuation operation) domain. Zhou et al. (2017) and Busoniu et al. (2008) proposed a novel asynchronous reinforcement learning algorithm that can solve problems such as exponential computation complexity in a large environment. Papoudakis et al. (2020) and Cheng et al. (2014) investigated several reinforcement learning algorithms and provided detailed experimental data, analysis, and insights into each algorithm.

Zhang and Yi (2015) simulated using robots to guide people evacuating from dangerous areas. In their study, the people guided by robots had a significantly shorter evacuation time than non-robot-assisted evacuation. As in the care home fires incident, people were unable to locate the fire location with closed room doors (Purser, 2015). With the help of guiding robots, people can find the exit rapidly even without prior training.

Wang et al. (2016) and Tan (1993) propose a shared-Q RL algorithm in crowd simulation, which could enhance the efficiency of crowd evacuation. Dong et al. (2020) applied a Rainbow Q-Network (DQN) to solve the multi-exit evacuation, improving data utilization and algorithm stability. Makinoshima et al. (2016) designed the RL scheme to solve the immersed tube tunnel problem of a fire evacuation.

In summary, RL is ideal for evacuation simulation because it can learn from interacting with the environment without prior knowledge, as the same criteria are needed in the emergency evacuation. During the emergency evacuation, there is no prior data that the agent can use. Agents have to learn by exploring the environment themselves and find the optimal evacuation route.

Multi-agent Reinforcement Learning

A multi-agent system (Papoudakis et al., 2010) can be referred to as "societies of agents," which is a set of agents that interact jointly to coordinate their behavior and often cooperate to achieve some collective goals (Gosavi, 2004). In most cases, the researchers usually used a single agent to complete exploration for an extremely long time. Instead of using Independent Reinforcement Learning (InRL), where each agent treats its experience as part of its environment, some researchers adopted a Multi-agent RL system (MARL) to define a range of collective situations (Lanctot et al., 2017; Shalev-Shwartz et al., 2016). Multi-agent learning is not simply adding more agents in the same environment; moreover, the interaction between each agent will significantly increase the complexity of the entire system. The behaviors between agents influence each other and accomplish the same goal through the internal cooperation mechanism. Researchers adopt this mechanism to combine the advantages of reinforcement learning to investigate a series of multi-agent reinforcement learning algorithms (Gwynne et al., 1999; Clouse, 1995).

Lanctot et al. (2017) compared agents' actions based on the observed behaviors. For the InRL, the policies learned by one agent overlaps other agents' findings, so InRL's learning policy can't be generalized to other agents. On the other hand, MARL can share learned policies with other agents. Balachandar et al. (2019) developed and evaluated different multi-agent protocols to instruct agents to collaborate to play soccer. They found that the model with communication had more promising results than the agents that didn’t have it.

In a MARL system, agents could interact while sharing common learned environment knowledge. They could either be competitive, cooperative, or a mix of the two. Martinez-Gil et al. (2011) used MARL to simulate pedestrian groups and the navigation process of the pedestrians. In their study, the researchers used two RL algorithms with multiple attributes for the simulation, including the group size and speed control. However, Martinez-Gil et al. (2011) suggested that two learning algorithms can be integrated into one for future research. The agents can better collaborate with one algorithm.

Raileanu et al. (2018) implemented the MARL algorithms with imperfect information. The reward of the RL in this study depended on both agents. Each agent has its hidden state, and the agent has to make predictions on other players from what they observed along with the experiment. Agents need to solve the task by the predictions they made. A unique approach called the self-other-modeling method was used in their study (Raileanu et al., 2018). In this approach, agents update the values of states and actions by incorporating the prediction of others' values of states and actions.

Many tasks, such as autonomous vehicles, multi-player games, and multi-agent navigation require multiple agents to interact and communicate. Agents need to learn to cooperate and achieve their goals more efficiently. While it may seem intuitive for human beings to cooperate and collaborate, the same cooperation process is more challenging for RL agents.

Shalev-Shwartz et al. (2016) implemented MARL into autonomous driving, where the vehicles need to form a long-term strategy that shares the same road with other traffic. The challenge of this study is the long duration of the experiment with different

other road users interrupting the regular operations. Shalev-Shwartz et al. (2016) used policy gradient iterations to deal with the interruptions. The interruption from other users is stochastic and unpredictable. The researchers used a hierarchical temporal abstraction in the policy gradient iteration (Shalev-Shwartz et al., 2016). To make agents easier to communicate and collaborate, it was found that having a decentralized controller may generate more desirable outcomes.

The centralized controller regards the whole system as one agent, which causes the state and action spaces to rise exponentially as more agents join the system (Balachandar et al., 2019), driving the decision-making process to become more challenging, computation becomes more complex. On the other hand, the decentralized controller could let agents communicate and collaborate individually (Balachandar et al., 2019). The decentralized controller treats every agent as an individual, eventually leading to more desirable results. De Witt et al. (2018) stated the possibility of complex decentralized coordination in the MARL when agents share some information.

Summary

In summary, there are numerous benefits for RL's application in analyzing a dangerous environment for evacuation. Multi-agent collaboration has tremendous advantages in utilizing RL across diverse fields of study. While existing studies have stressed the significance of multi-agent collaboration, few studies concentrated on the application of multi-agent collaboration using RL for navigation and exploration during an emergency evacuation, especially with unknown threats in the environment. This study was intended to fill the gap by investigating the effect of multi-agents and

environment complexity on the evacuation efficiencies, both under the static obstacles and dynamic obstacles situations, for an airport environment situation.

Methodology

This section describes the research approach and methodology, including the learning environment, algorithm, and data treatment and analysis. There was a sequence of two studies conducted for this project. Study 1 investigated the performance difference between a single-agent and a multi-agent method for a static obstacle situation; study 2 was based upon the results obtained from study 1 and extended to a more aviation specific application. In study 2, a small airport was used as the environment and the threats were modeled as moving. Study 2 investigated performance differences in a dynamic environment, when obstacles are moving in a more airport specific environment.

Research Approach for Study 1

For Study 1, there were two types of environments explored by robot agents, including single-agent exploration and multi-agent collaboration, their goal was to investigate the environments and locate the exits as soon as possible. The performances of single-agent exploration and multi-agent collaboration during emergency evacuation using RL algorithms were compared. The complexity of the environment and the exploration method were the two independent variables, and each of them had two levels. The dependent variable for this study was the performance of the agents. The agents'

performance would be compared in different situations regarding time, death counts, and rewards.

Design and Procedures

Two different environments were used as the test bed for exploration. A simple environment was a 10*10 meters space with one threat, and a complex environment was a 10*20 meters space with three threats. Agent/agents started from the left lower corner of the map to try to locate the room's exit. There were threats with a dimension of two by three in the middle of the room placed randomly, and one unit to each direction around the threat was considered the dangerous area, as shown in Figures 1 and 2.

The figures show that the cross and circle were the beginning and the ending points, respectively; the dark blue and light blue areas were the threat and the dangerous regions. Agents would try to learn and evacuate while avoiding the hazardous area and the danger.

Figure 1

Simple Environment

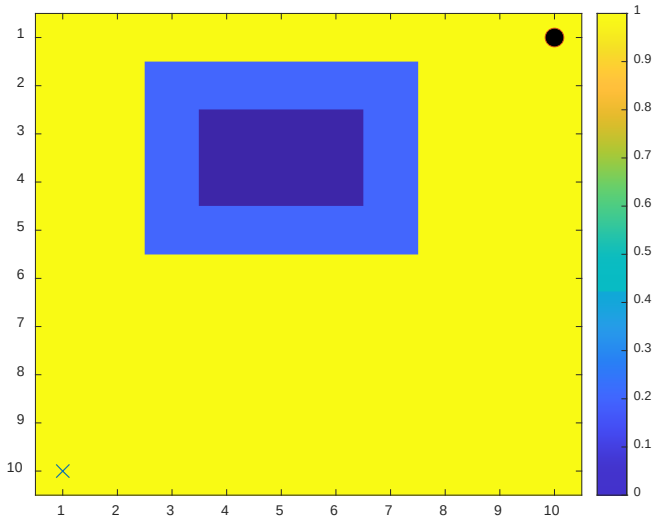
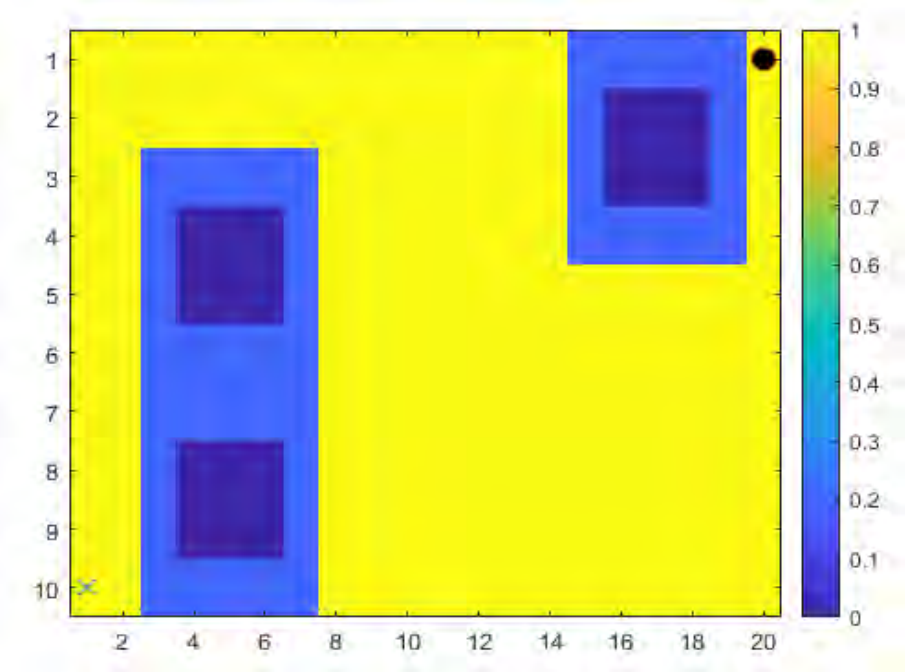


Figure 2

Complex Environment



A single Q-table was employed in the single-agent simulation to record the rewards and actions. The number of maximum episodes was 5000. For multi-agent simulation, two agents both started at the origin point. They would communicate and collaborate by sharing the Q-learning table. Each agent would update its own Q table, and the final Q-table would be the average of the two individual Q-learning tables. The research operated each scenario 50 times for statistical analysis to see the differences between single-agent exploration and multi-agent collaboration methods. Each trail would end after 5000 episodes, and then agents would start over to explore the environment.

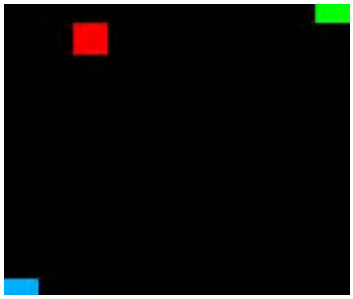
The agents could move in eight directions freely. Thus, there were eight potential action choices for each position, except at the corners or edges.

Research Approach for Study 2

In a dynamic environment, the obstacle is simulated to move continuously. To implement the Q-learning method for study 2, we used a similar layout as Study 1, and assume there are two agents starting at the entrance of a room, the room has the size of 10*10 meters, the obstacle is moving within a known trajectory which is a 9*9 square trajectory. The agents are trying to find the exit without colliding with the obstacle. Each agent uses the Q-table to record the state status and the action taken. The state status is agent location, measured by the distance between the agent and the target and the distance between the agent and the moving obstacle. The map is shown as the following Figure 3.

Figure 3

Moving threats dynamic environment

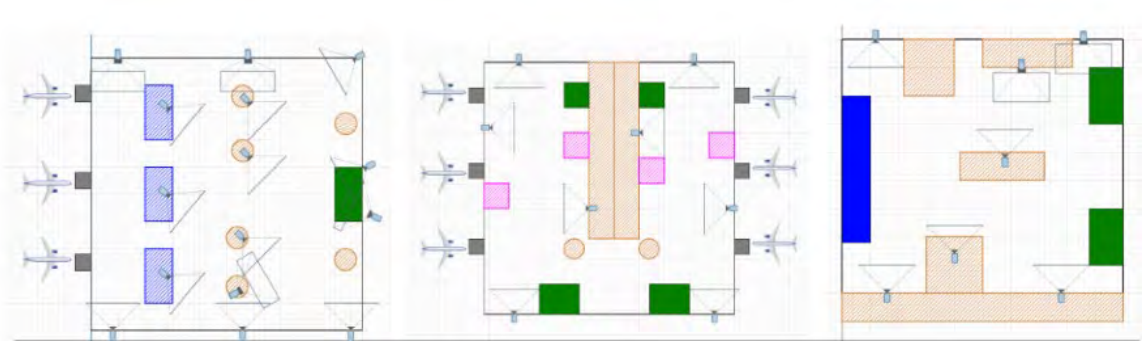


As shown in Figure 3, the blue square is the beginning point, while the green square is the target point. The red square is the obstacle area and once the moving agent collides the red area, the agent will go back to the beginning point. In this study's dynamic environment, the obstacle was moving with a square trajectory, while we set the agent moving to eight different directions as default, which means there are eight possible actions choice for every state.

Furthermore, a real airport environment was used as the environment to demonstrate the benefits of the MARL in dynamic environment. The environment is shown as the following Fig.4.

Figure 4

Three airport environments



In the airport environment, a moving threat was initialized in a random position and moving at a random direction every time step. For these three maps, two agents were applied to explore and evacuate to the exit on the upper right. The reward scheme was same as indicated in study 1. Two types of agent interactions were compared, one was the two agents explored environment independently without any collaboration and the second way is have the two agents' communication and collaborate simultaneously, as described in first phase of the study 2. The average reward was compared between these two methods for all the three different airport layouts.

For both studies, a Q-learning RL algorithm was used to find the best policy to maximize the reward, and Python simulated and compiled the result, described in the next section.

Q-Learning Algorithm

In both studies, Q-learning was utilized as an off-policy RL algorithm that seeks to find the best action for the current state. The Q-table includes states and actions, which follows the form of Q (state, action), as shown in Table 1 as a sample format. States and actions would be preserved in the Q-table, and agents would take actions based on the Q-value. Performance measures were collected including time, death counts, and rewards.

Table 1

Q-table

State/Action	A_1	A_2
S_1	Q (s_1, a_1)	Q (s_1, a_2)
S_2	Q (s_2, a_1)	Q (s_2, a_2)
S_3	Q (s_3, a_1)	Q (s_3, a_2)

Agents are required to discover the policy that maximizes the expected cumulative rewards. The bellman function is employed to find the optimal decision sequence. The current state value function V(s) could be acquired by computing the total reward of the current state's expected reward. The bellman function is shown below:

$$V\pi\,(s)=E\,(Ut \mid St = s)$$

$$= E\,[R(t+1) + \gamma\,[R(t+2) + \gamma\,[\ldots\ldots]] \mid St = s] \quad (1)$$

$$= E\,[(t+1) + \gamma\,(S') \mid St = s]$$

The $V^*(s)$ is the maximum cumulative expected value:

$$V^*(s)= max_\pi\, V_\pi\,(s) = max_\pi\, E\,[\sum_{t=0}^{H} \gamma^t\, R(s_t, A_t, S_{t+1}) | \pi, s_0 = s] \quad (2)$$

The state-action function is:

$$\boldsymbol{q_\pi(s,a) = E_\pi[r_{t+1} + \gamma r_{t+2} + \ldots . | A_t a, S_t = s] = E_\pi[G_t | A_t = a, S_t = s]} \quad (3)$$

The Gt is the total discount reward value for time t and γ is the discount factor. When the discount factor is close to 1, the latter state is more critical; vice versa, when the element is close to 0, the agent only considers the current interest's influence. The best action-value function (4) was utilized to open the expectation (5):

$$\boldsymbol{Q^*(s,a) = max_\pi\, Q^*(s,a)} \quad (4)$$

$$\boldsymbol{Q^*(s,a) = \sum_{s'} P(s'|s,a)(R(s,a,s') + \gamma\, max_{a'}\, Q^*(s',a'))} \quad (5)$$

The solution is thus:

$$\boldsymbol{Q_{k+1}{}^*(s,a) \leftarrow \sum_{s'} P(s'|s,a)\big(R(s,a,s') + \gamma Q_k{}^*(s',a')\big)} \quad (6)$$

The advantage of Q-learning is employing the Temporal Difference (TD) learning method and offline learning for agents.

The TD learning incorporates the sampling method of the Monte Carlo method and the bootstrapping of the Dynamic programming method, which operates the latter state's value function to estimate the current value function. These features make TD fit in the model-free algorithm and accomplish the goal faster. The value function is presented as follows:

$$\boldsymbol{V(s) \leftarrow V(S) + \alpha\big(R_{t+1} + \gamma V(s') - V(s)\big)} \quad (7)$$

The $R_{t+1} + \gamma V(S')$ is called the TD object, and the $\delta_t = R_{t+1} + \gamma V(s') - V(s)$ is called the TD bias.

The Q value can be calculated according to the formula (8). This is the renewal process of the Q-table.

$$Q(s,a) \leftarrow Q(s,a) + \alpha[r + \gamma\, max_{a'}\, Q\,(s',a') - Q(s,a)] \quad (8)$$

The formula above is the update function of the Q-learning. The agents would select the max Q (s', a') multiplied by the discount rate and then add the real reward value as the Q-reality based on the following state: s.' The previous Q-value in the Q-table would be the Q-estimate.

$$\boldsymbol{Q(s_1,a_2)}_{\text{reality}} = \boldsymbol{R + \gamma * max\, Q\,(s_2)}$$

$$\boldsymbol{Q(s_1,a_2)}_{\text{estimate}} = \boldsymbol{Q(s_1, a_2)}$$

$$\boldsymbol{Q_{difference} = Q_{reality} - Q_{estimate}}$$

$$\textbf{New}\boldsymbol{Q(s_1, a_2) = Old(s_1, a_2) + \alpha * Q_{difference}}$$

The loop would then be generated to calculate the final Q-table. The pseudocode of the Q-learning algorithm shown below was used:

Algorithm 1 Pseudocode of the Q-learning

Initialize *Q(s, a)* arbitrarily

Repeat (for each episode):

  Initialize *s*

  Repeat (for each step of the episode):

    Choose *a* from *s* using policy derived from Q (e-greedy)

    Take action *a*, observe *r*, *s'*

    $Q(s,a) \leftarrow Q(s,a) + \alpha[r + \gamma\, max_{a'}\, Q\,(s', a') - Q(s,a)]$

    $s \leftarrow s'$

  Until s is terminal

The general algorithm for multi-agent was derived from the single-agent Q-learning. For the multi-agent algorithm, agents would examine the environment jointly

and renew the same Q-table. The shared Q-table was their communication method for collaboration. The pseudocode of the multi-agent Q-learning algorithm is shown below:

Algorithm 2 Pseudocode of the Multi-agent Q-learning

Initialize $Q\ (s_1, a)$ arbitrarily

Initialize $Q\ (s_2, a)$ arbitrarily

Repeat (for each episode):

Initialize s

Repeat (for each step of the episode):

Choose a from s_1 using policy derived from Q_1(ε-greedy)

Choose b from s_2 using policy derived from Q_1(ε-greedy)

Take action a, observe r, s'

Take action b, observe r_2, s_2'

$Q1(s1, a) \leftarrow Q1(s, a) + e\ act \max_{a'} Q\,1(s', a')ass, a) + e\ a$

$Q1(s1, b) \leftarrow Q1(s1, b) + \alpha[r + \gamma\, max_{a'}\ Q\,1(s2', b') - Q1(s2, b)]$

$s \leftarrow s'$

Until s is terminal

Results

This section presents the results for both studies, including the agents' performances, including time, death counts, and reward. The results of single-agent exploration and multi-agent collaboration were presented for both studies. For study 1, a

statistical analysis was conducted to compare the differences between the different conditions, for study 2, graphical illustrations were used to clearly show the gap in rewards between the two agents exploration methods.

Study 1 Results

The results of agent exploration time, death counts, and reward for the simple and complex environment with/without collaboration are exhibited in Table 2. Time, death counts, and reward were the average result through 5000 episodes.

Table 2

Descriptive Statistics Between Simple and Complex Environment

Environ-ment	N = 50	Collab. Time (s)	No Collab. Time (s)	Collab. Death	No Collab. Death	Collab. Reward	No Collab. Reward
Simple	Mean	24.099	30.116	.009	.140	-36.280	-44.273
	SD	.180	.444	.001	.006	.043	1.496
Complex	Mean	137.415	616.215	.102	2.466	-82.820	-364.295
	SD	7.063	22.348	.007	.099	.048	18.834

Note. Collab. = Collaborative method, *SD* = Standard Deviation

Hypothesis Testing

From the results above, it can be seen that the environment has some influences on the performance of agent collaboration; three two-way ANOVAs were performed to further test the effect of collaboration and environment on the agent learning performance, in terms of time, death counts, and reward between collaboration and no-collaboration methods, and the interaction effect on these measures between the collaboration method and the complexity of environments. The assumptions of equality of variance were tested. Levene's tests of equality of variance were significant ($p < .05$), and thus unequal variances were assumed for all three ANOVAs. Three two-way between-subjects ANOVAs and interaction effects were all significant at the alpha level

of .05, $p < .001$; the results are shown in Table 3. The time for agents with collaboration to find the exit was significantly lower than the agent without collaboration in both environments.

Two null hypotheses were thus rejected. There was a significant difference in the performance between single-agent exploration and multi-agent exploration regarding time, death counts, and rewards. There were interactions between the complexity of the environment and the performance, including time, death counts, and rewards.

The death counts for agents with collaboration were significantly lower than those without collaboration in both environments. The reward for collaborating agents was substantially higher than the agent without collaboration in both environments. Figures 5, 6, and 7 below show all three positive interactions. The agents' performance, including evacuation time, death counts, and reward, increased when the environment became more complicated (0 refers to simple environment and single agent without collaborations).

Table 3

Two-Way ANOVA for Environment, Collaboration or Both

DV	Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Time	Environment	6114755.287	1	6114755.287	44506.830	.000
	Collaboration	2938105.373	1	2938105.373	21385.280	.000
	Environment * Collaboration	2794053.190	1	2794053.190	20336.783	.000
Death Count	Environment	73.136	1	73.136	29626.705	.000
	Collaboration	77.785	1	77.785	31510.208	.000
	Environment * Collaboration	62.278	1	62.278	25228.536	.000
Reward	Environment	1679604.422	1	1679604.422	18821.675	.000
	Collaboration	934902.948	1	934902.948	10476.538	.000
	Environment * Collaboration	1047398.477	1	1047398.477	11737.165	.000

Figure 5

Interaction Between IVs Regarding Time

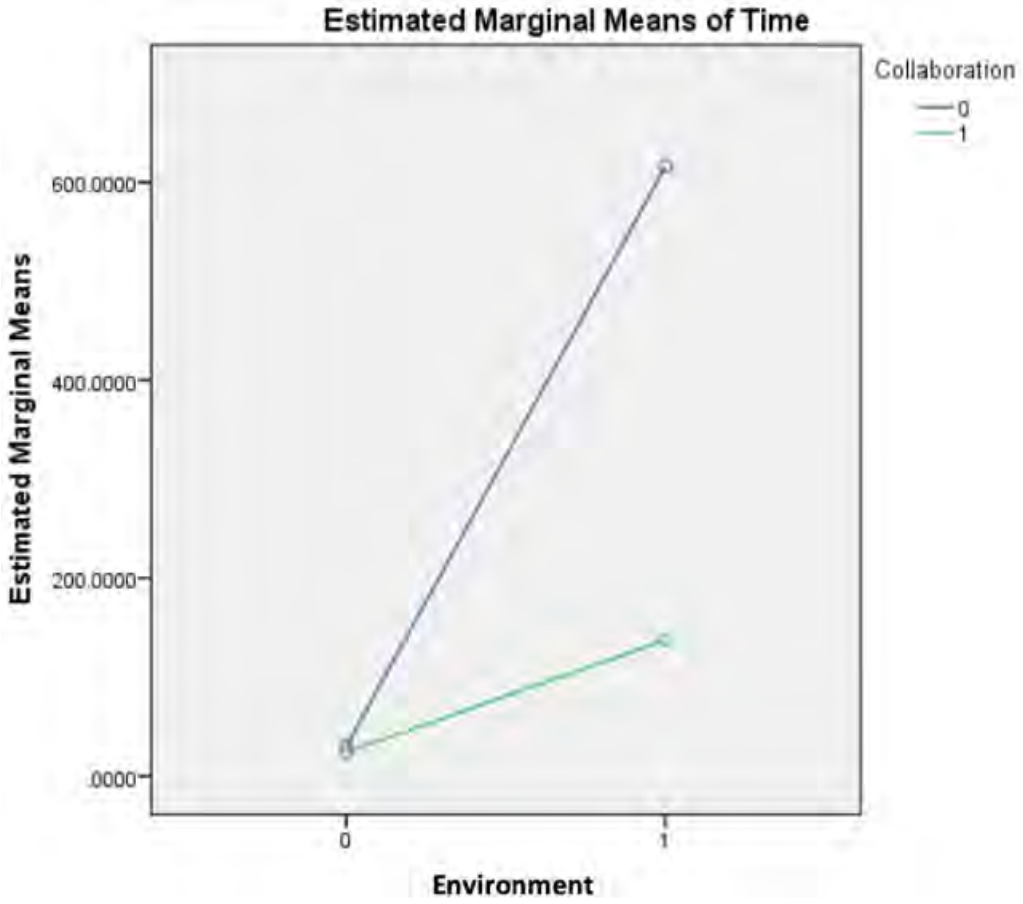


Figure 6

Interaction Between IVs Regarding Death Counts

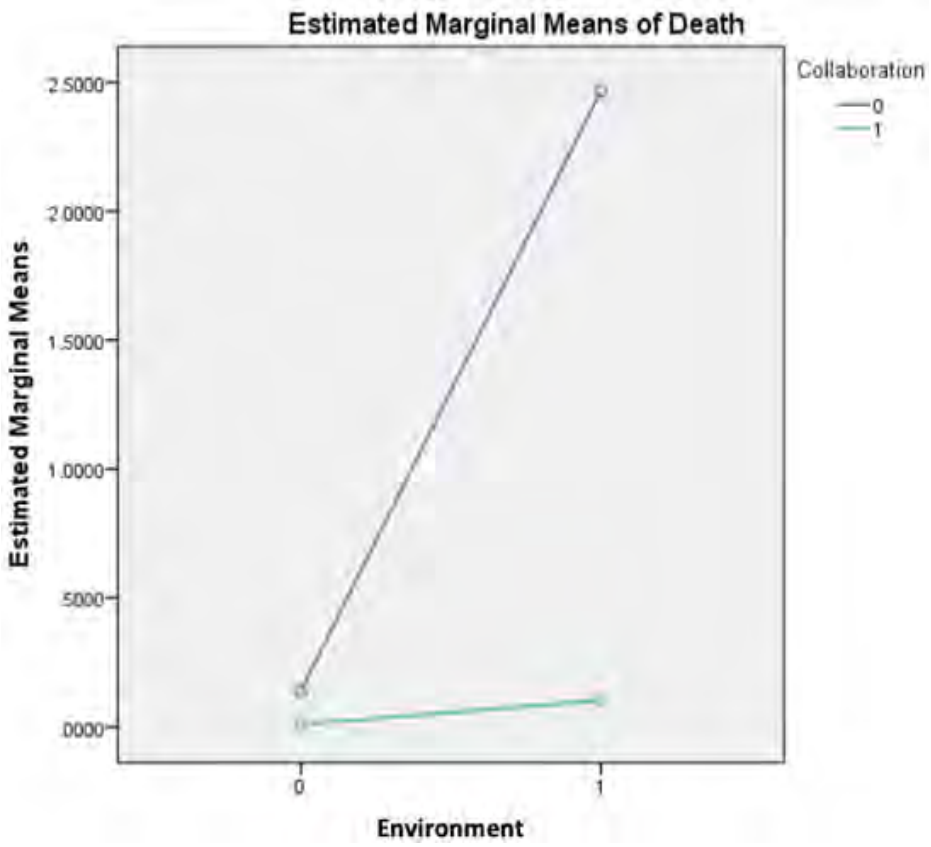
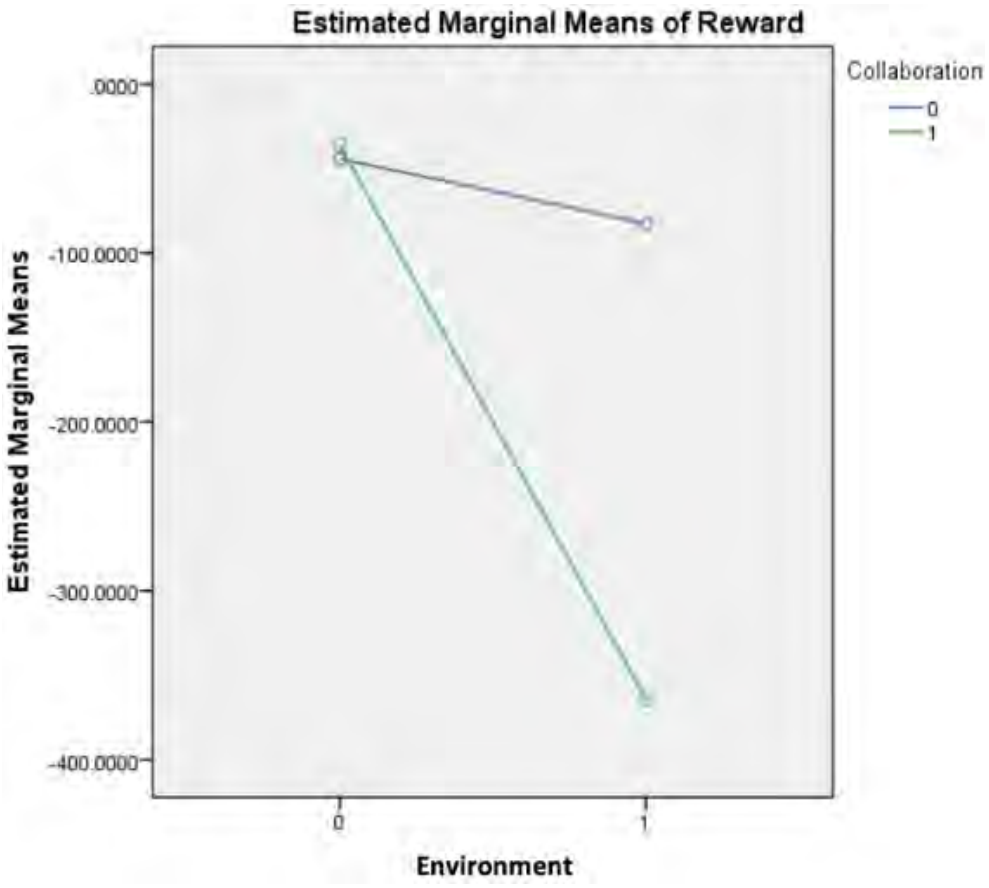


Figure 7

Interaction Between IVs Regarding Reward



Exploration Behaviors

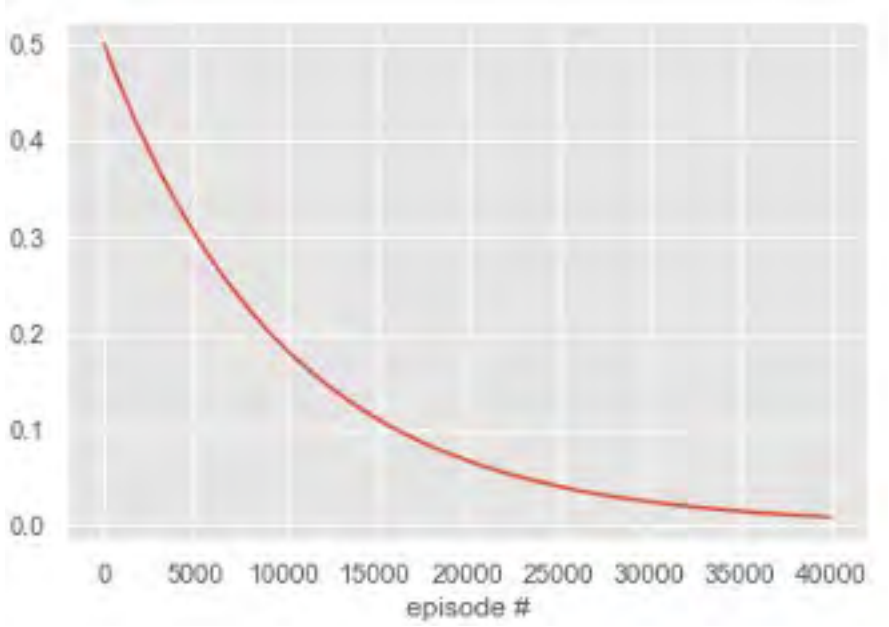
Agents are set to move in eight different directions as default, which suggests there are eight possible choices for every state. With the exploration and exploitation strategy, the experiment initialized the exploration rate as 0.5, while the exploration rate will be 0.9999. The formula for the exploration and exploitation will be:

$$\varepsilon = (0.9999)^{Episodes} * 0.5$$

The exploration rate based on the episodes is shown in Figure 8, with a maximum episodes of 40000:

Figure 8

Exploration Rate and Episodes

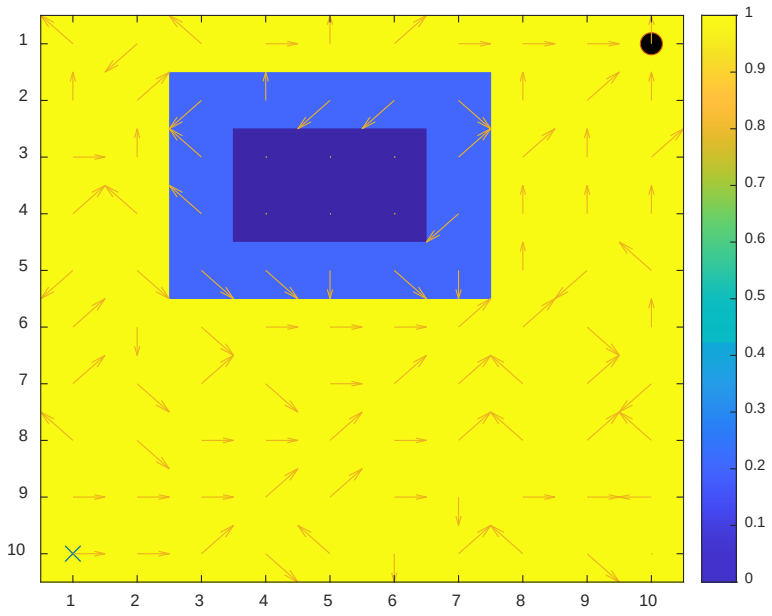


Study 1 Single Agent Exploration Behaviors

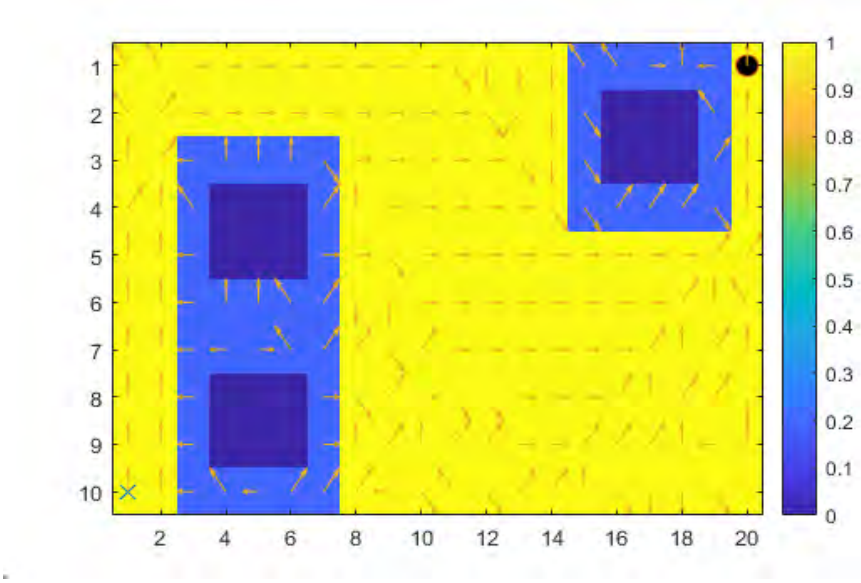
Figure 9 displayed the final actions on each position (state), and Figure 10 highlighted the learned best route (policy) for the evacuation. The agent starts with random exploration, and after several episodes, specific actions would be bypassed, and eventually, the optimal policy was learned.

Figure 9

Agents Choices for Each Position in Simple or Complex Environment



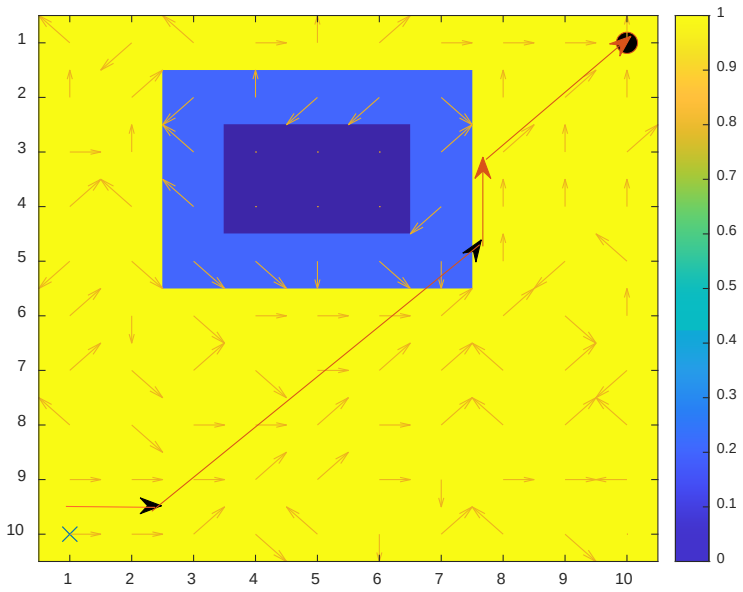
Note. Simple Environment



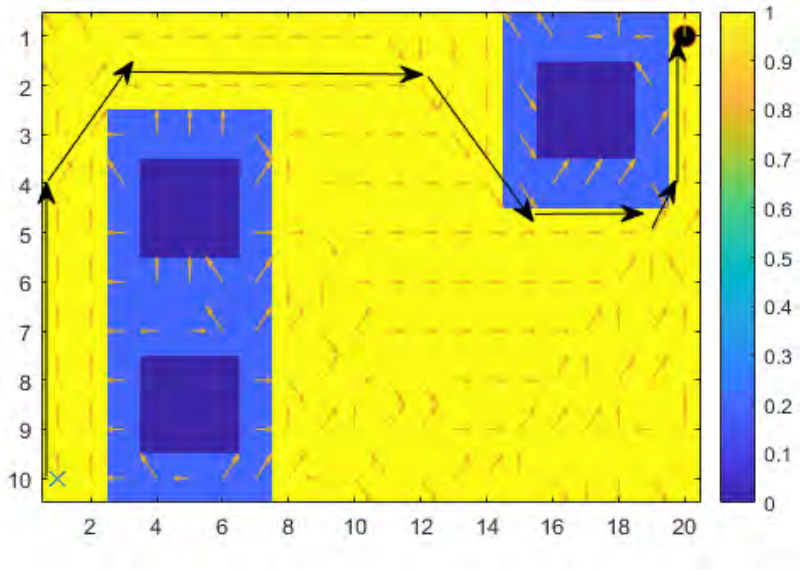
Note. Complex Environment

Figure 10

Optimal Route for Evacuation in Simple or Complex Environment



Note. Simple Environment

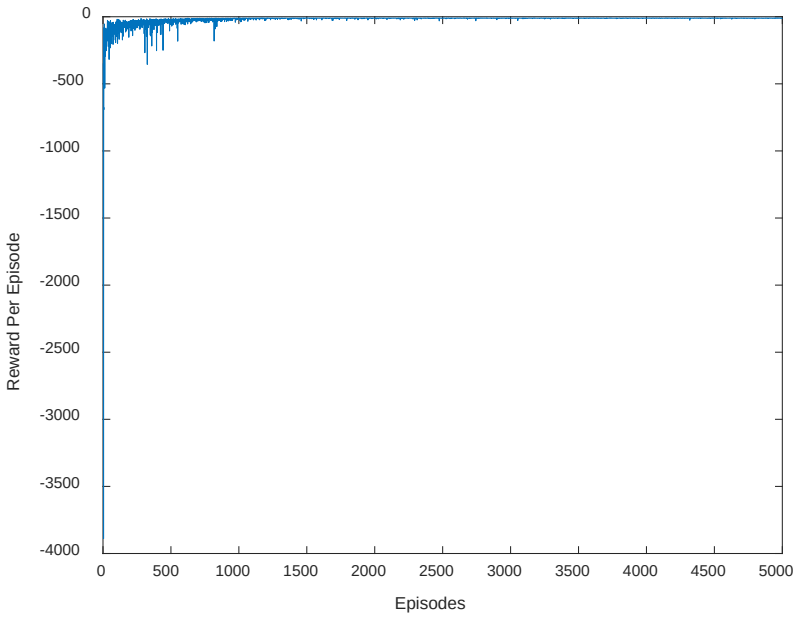


Note. Complex Environment

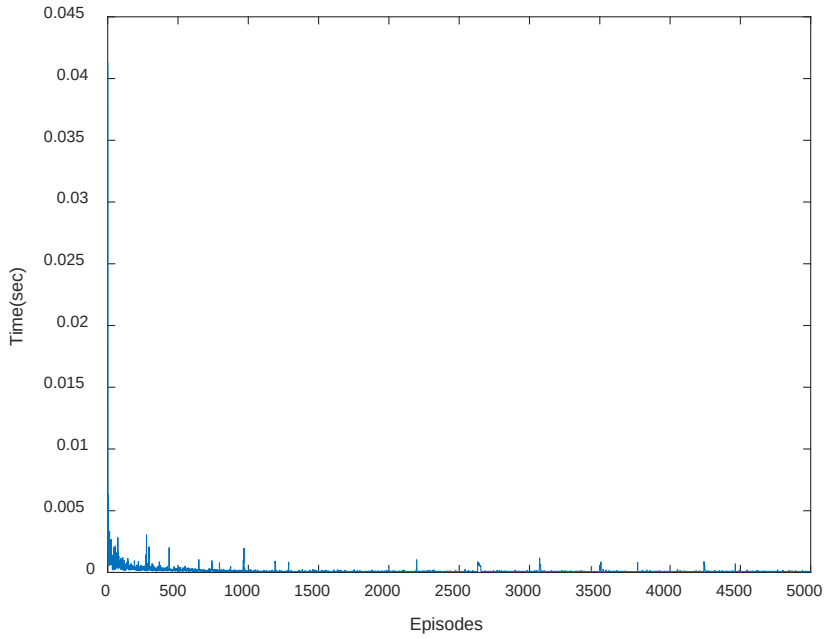
Figure 11 depicts the rewards and time for the simple and complex environment. From Figure 11, the learning performance constantly improved until 500 episodes, and after that, the improvement of learning diminished to a plateau steady state. The computation time dropped sharply in the simple environment and stabilized after 1000 episodes. The time in the steady-state period was lower than 0.005 seconds per episode. In the complex environment, the agent followed a similar pattern as in the simple environment, except the agent needed a long time to learn from the environment. The reward increased continually in the first 1000 episodes and became stable around 3000 episodes. The cumulative reward was slightly lower, and the time was slightly higher than in the simple environment. The time was not as steady as those of the simple environment. The higher complexity level caused this unsteady environment and the insatiable policy's choice.

Figure 11

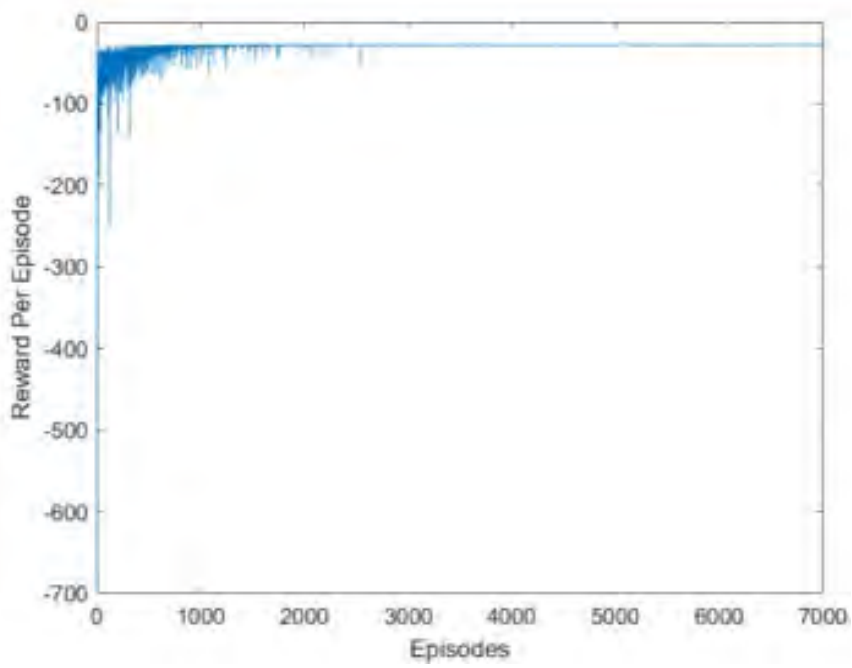
Reward and Computation Time in Simple and Complex Environment



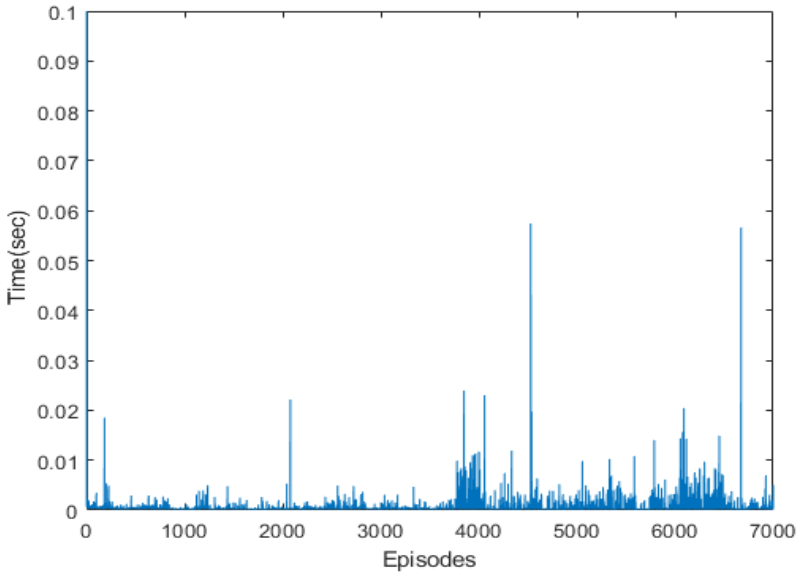
Note. Time in Simple Environment



Note. Time in Simple Environment



Note. Reward in Complex Environment



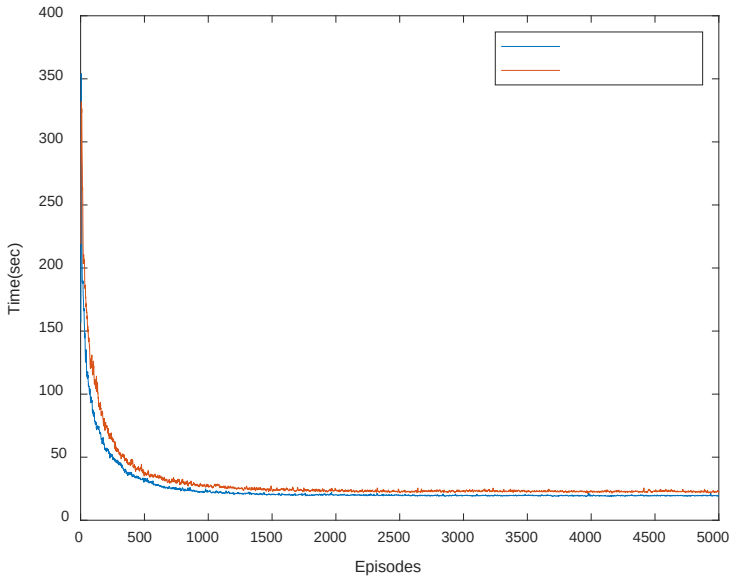
Note. Time in Complex Environment

Study 1 Multi-Agent Collaboration Behaviors

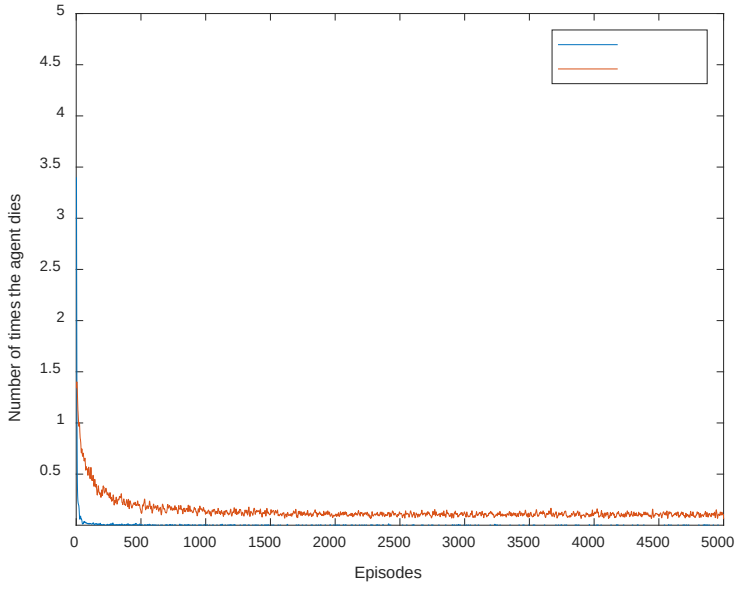
The mean value of fifty trials and a moving average filter was utilized to demonstrate the main effects. The results are displayed in Figure 12. The red line represented the result for no collaboration exploration, and the blue line represented the collaboration exploration. The left figure showed the time, and the right figure showed the number the agent touched the threat and died.

Figure 12

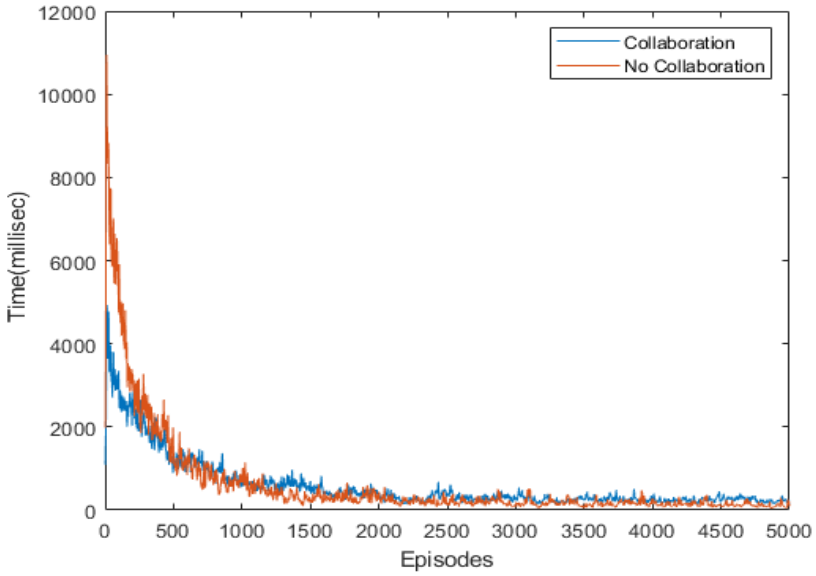
Time and Death Counts With/Without Collaboration in Simple and Complex Environment



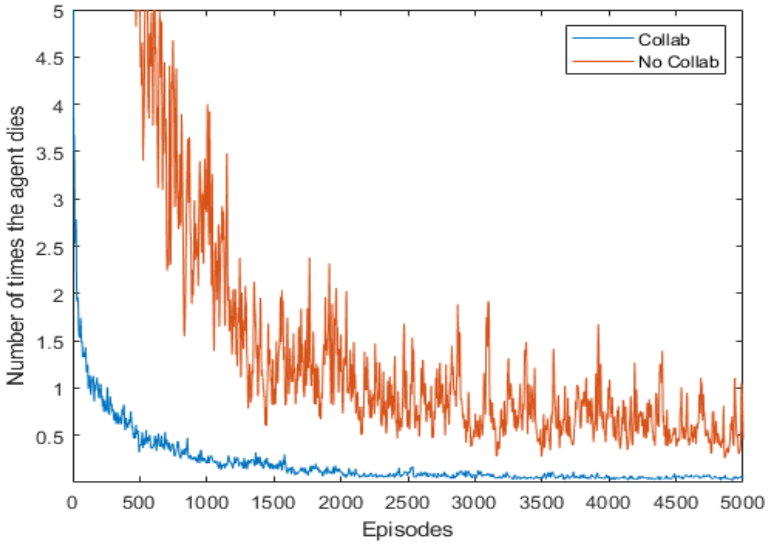
Note. Time in Simple Environment



Note. Death Counts in Simple Environment



Note. Time in Simple Environment



Note. Death Counts in Simple Environment

It is fairly straightforward to visualize for simple and complex environments, and collaboration outperformed the non-collaboration agents. More specifically, for the simple environment, the time for agents with collaboration to converge to the optimal policy and reach a stable value was much faster than non-collaboration agents, the

collaboration's method needs 19.46 milliseconds agents without collaboration used 22.8 seconds, which improved by 17.6 percent. In the complex environment, agents with collaboration had similar steady-state values, but agents with collaboration converged to the stable value faster.

In the simple environment, the tendency of touching the threat was similar between the agents with and without collaboration. However, it can be noticed that the number of threats touching agents with collaboration dropped much faster than those of the agents with no collaboration.

The advantage of the collaboration for agents to avoid the threat was much more pronounced in the complex environment than in the simple environment. From Figure 9, it can be observed that the probability of death in the collaboration model dropped much faster than in the non-collaboration model. As the environment became more complex, the benefits of the collaboration became more prominent.

Study 2 Results

The result of study 2 showed a similar benefit for multiple agent collaboration. In this study, it was found that the main benefits for multiple agents collaboration is in the time to converge to the steady state, and the rewards profiles are similar. After examining an exploitation strategy and implementing the Q-learning algorithm into this experiment, study 2 adopted the heat-map statistic method to obtain the final route computed by the Q-learning algorithm, to take a deeper look at the agent behaviors, as shown in Figure 13.

Figure 13

Heat-Map of Agent Movement vs. Obstacle Movement

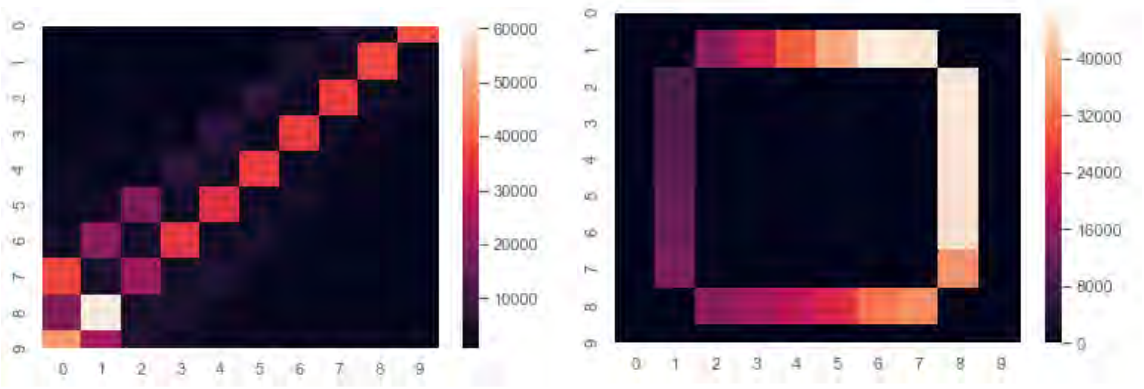
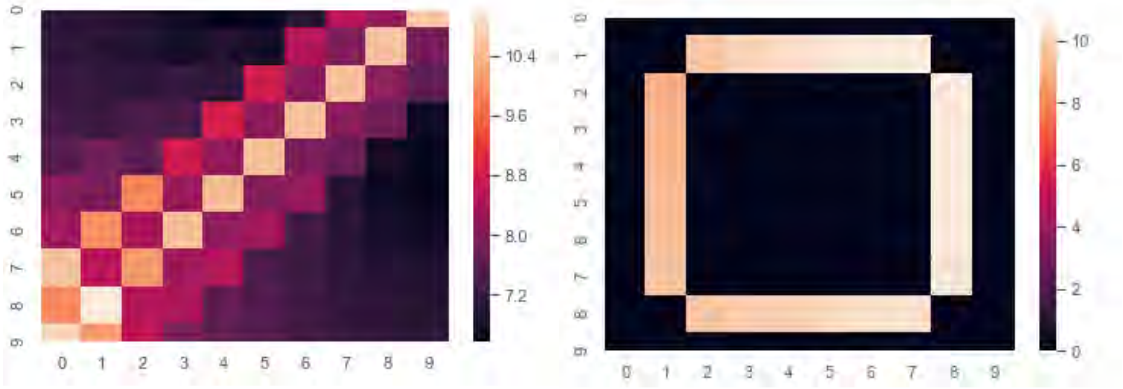


Figure 13 exhibits the obstacle and the agent's movement, demonstrating that the agent followed the diagonal route to evacuate. Agent finally reached everywhere on the 10*10 map; the reason for the map concentrated on this diagonal line is that the agent spent more time on this optimal route than any other position. The common log transformation was adopted to avoid the skewed distributions of state visits. The formula for the log transform is: $= log(x + 1)$, where x is the number of times an agent passes a location. After doing the log transformation, the second heat-map is generated for the agent and the obstacle movement, as following Figure 14, which ended up with a smoother distribution:

Figure 14

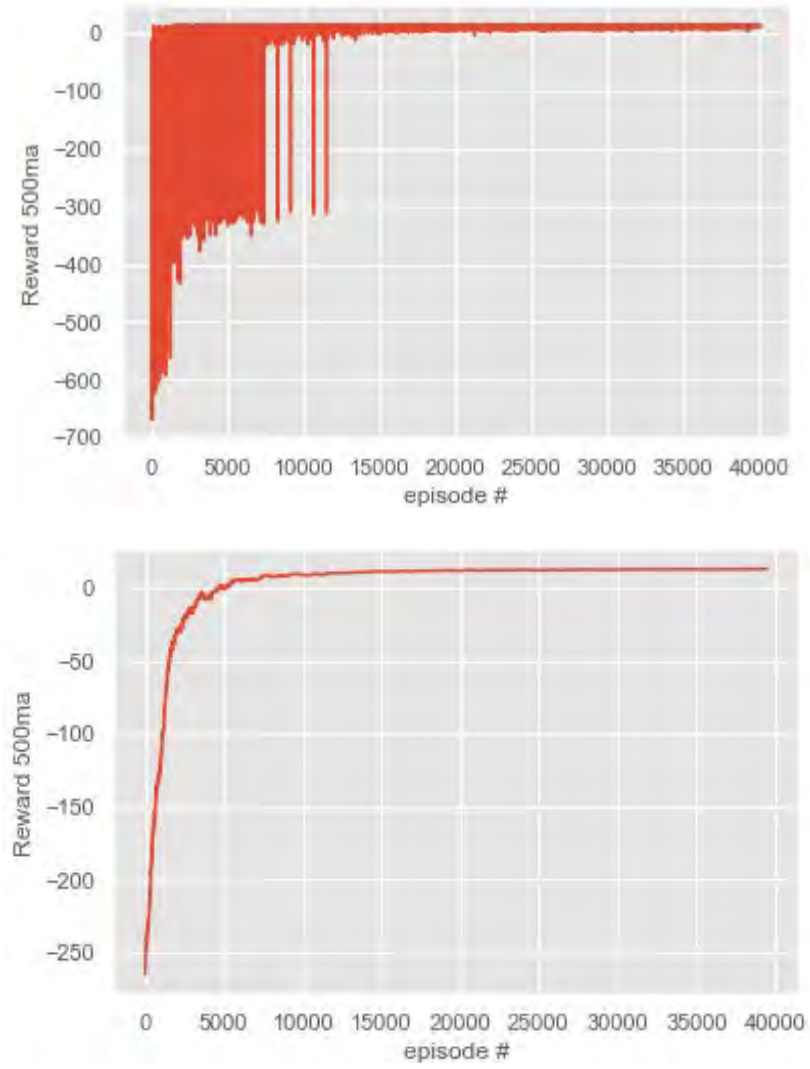
Heat-Map of Agent Movement vs Obstacle Movement (After Log Transform)



The experimental data has improved particularly in the first 5000 experiments. Because the reward for each episode is zero at the start of the training, the agent will presumably move randomly so that the reward gradually changes based on every episode, sometimes these changes can be abrupt due to the different level of randomness involved. In this study, in order to observe the overall trend, the moving average algorithm was implemented by the NumPy convolution to smooth the reward curve, in order to better visualize the results. For the moving average, a time window is slid along with the input and compute the mean of the window's contents. The comparison between the reward curve and the reward curve after running means is shown in Figure 15:

Figure 15

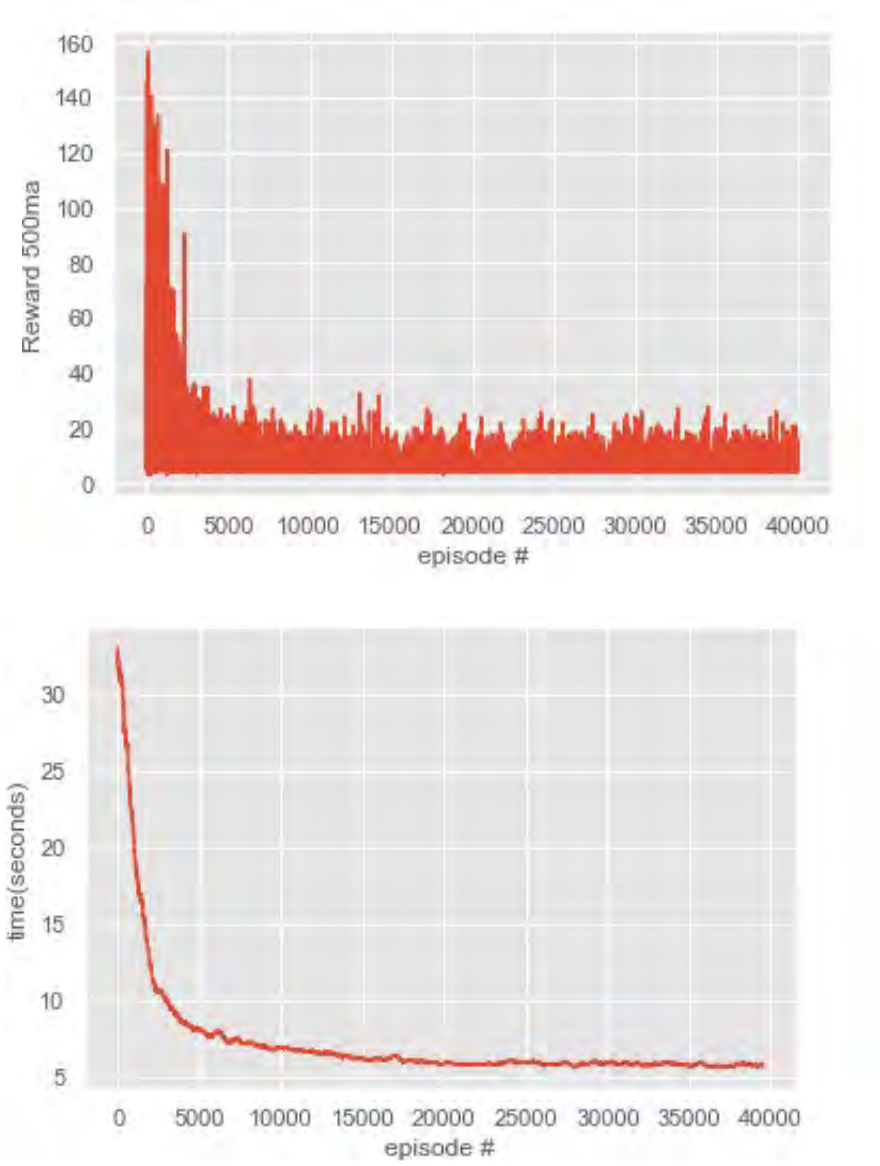
Original Reward Curve vs. Smoothed Reward Curve



The moving average computation time value is around five milliseconds per episode, the running time to achieve steady-state is shown in Figure 16:

Figure 16

Computation Time Curve vs. Running Mean Computation Time

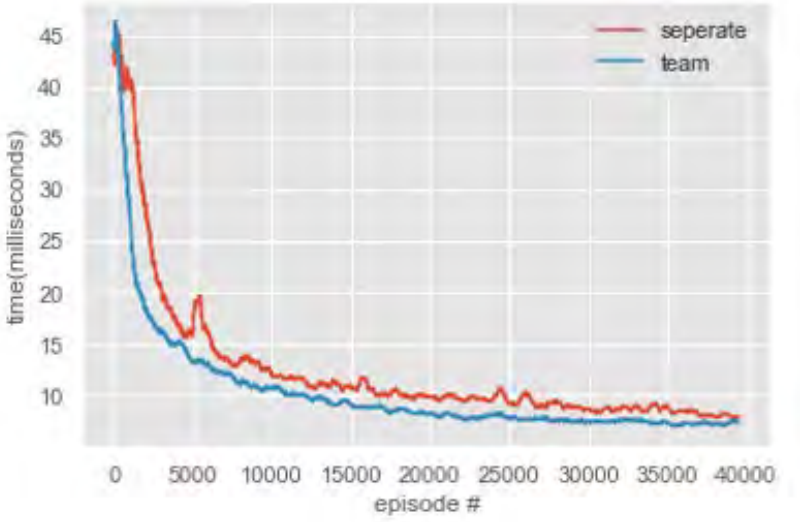


The two agents start simultaneously in the beginning, and they mostly likely went in different directions, due to the random initial actions. During the learning phase, they updated the Q-learning table simultaneously, and shared Q-learning table data with each other. So it is expected that final Q-table converged much more rapidly than the case without collaborations. This experiment compared the two agents moving to the target

separately and the two-agent moving to the target by using the collaboration algorithm. The computation time is being compared in Figure 17.

Figure 17

Episodes Over Time for Collaboration vs. Separate



In Figure 17, the red line represents the no-collaboration case, whereas the blue line represents the collaboration case. The figure shows that the blue curve drops and reaches a stable value faster than the red curve, and the calculation time is shorter to get the steady state. The collaboration's method cost 6.5 milliseconds per episode. However, the no-collaboration one costs 7.5 milliseconds per episode, which improves 15.4 percent. And from the curve, with the training progress, the computation time curve of the collaboration is found to be smoother than the separation one. That implies that the collaboration algorithm is a little more stable in converging to the optimal policy. And it is worth noting that in this situation, the size of the room is only 10*10 meters; with the increasing size of the map, the collaboration method could be more effective.

Figure 18-20 show the comparison results for the real airports simulations based on Figure 4.

Figure 18

Airport layout 1 reward comparison

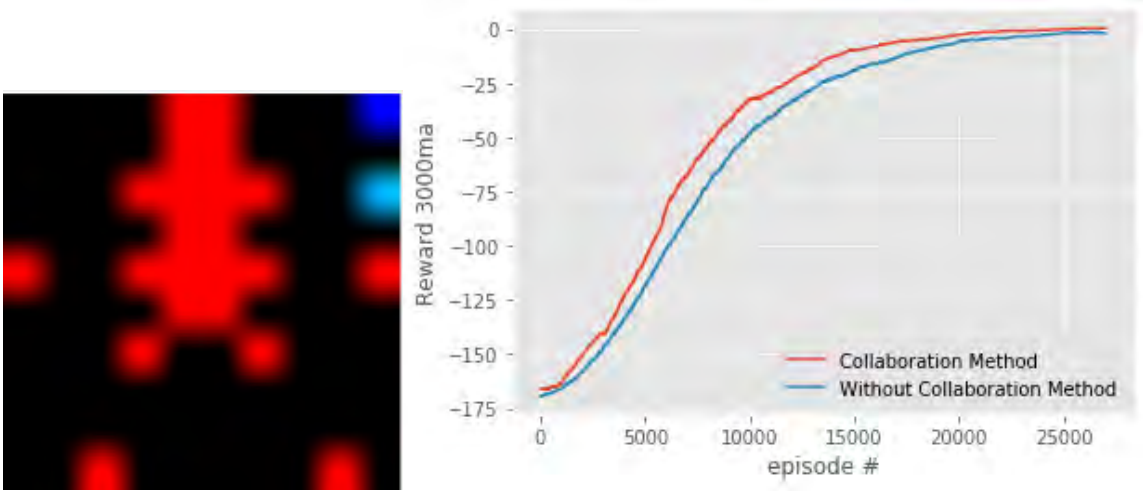


Figure 19

Airport layout 2 reward comparison

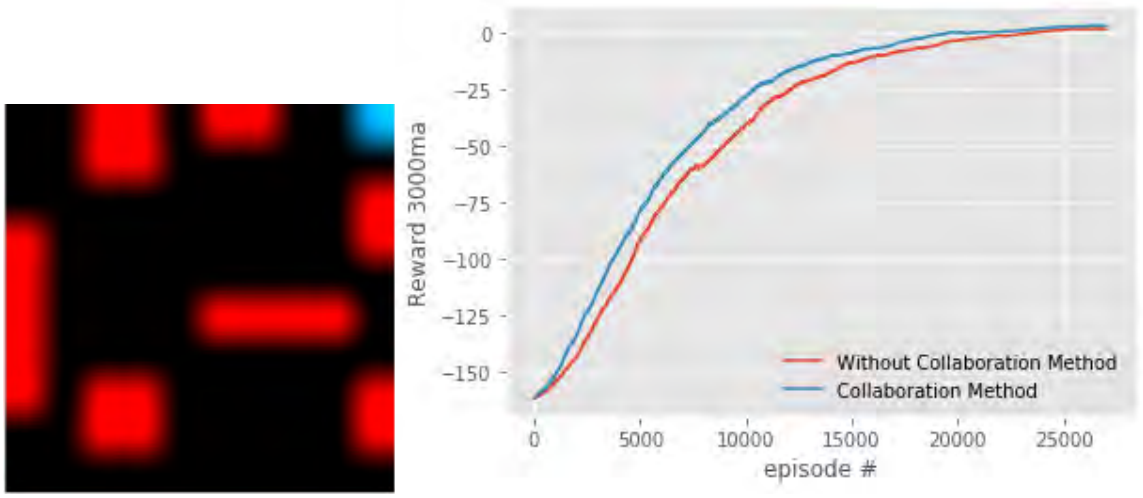
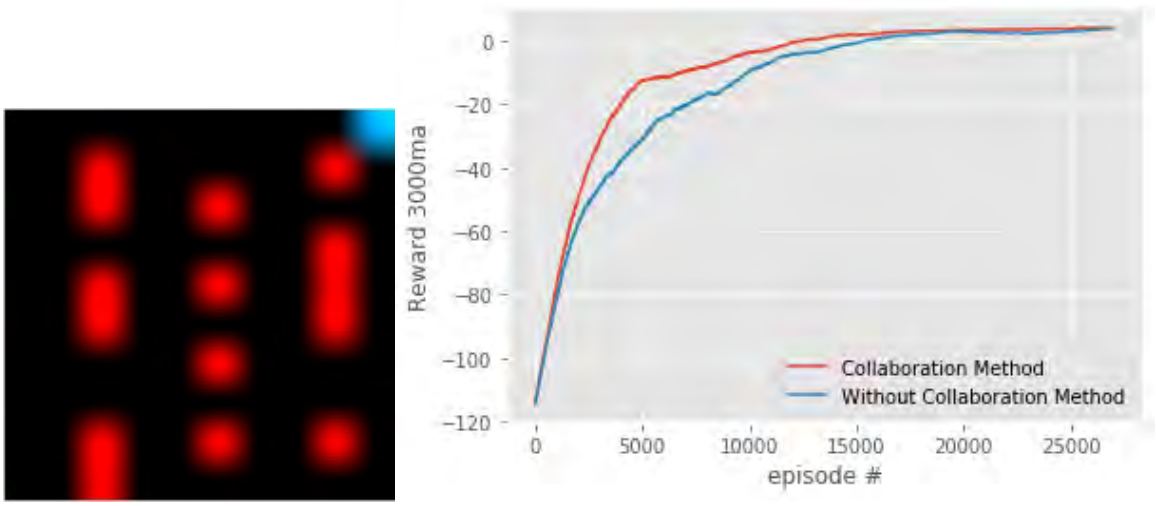


Figure 20

Airport layout 3 reward comparison



From the experiments with three airport layout maps, it can be seen that the collaboration showed a similar benefit for all three maps. Although both methods achieve similiar results after 25000 episodes or so, the results implied that they can both successfully converge to the optimal evacuation policy, however, from the three plots, the collaboration case converges much faster. This is the same as the previous case with 10 *10 room experiment. With a more complex environment like the airport, with more obstacles involved, multi-agent collaboration demonstrated efficiency in learning the evacuation route, implying saving times to find the best evacuation route.

Discussion, Conclusions, and Recommendations

Discussions

An emergency could happen anytime at any place. Under urgent circumstances, it is hazardous and time-consuming for evacuees to identify the most proper route, especially if there are some uncertainties and life-threatening conditions in the surroundings, more so if the evacuees are not familiar with the environment. The public may panic during the evacuation and exhibit flawed decision-making capability. For the transportation system with high pedestrian density, the insufficiency of training and assistance will cause significant chaos and congestion. Training can be added and emphasized during daily operations, but different kinds of assistance should also be in place to deal with the crisis whenever necessary. The use of autonomous agents for exploration could save time and minimize the risk for human beings. The agents can quickly examine the unfamiliar environment and form the optimal evacuation route from learning, and these routes can be communicated to humans to guide the evacuation process.

Using the RL algorithm, this study used robotic agents to model the navigation process in an unknown environment. Agents can learn the environment quickly, find the optimal evacuation route efficiently and avoid threats effectively. Two types of environments, simple and complex, and two types of agent interaction, collaboration or no-collaboration, were compared to investigate their effects on the learning performance. Results discovered that the multi-agent collaboration algorithm delivered a significantly better performance than the single-agent method regarding the time needed to locate the

exit and the reward which were calculated by total steps and punishments in both simple and complex environments. The differences were much more evident in the complex environment.

The RL agents learned the optimal policy from the environment through trials and reinforcement. Time is critical during an emergency evacuation. The efficiency of learning depends on the knowledge of the environment; the more knowledge about the environment, the faster an agent converges to the optimal navigation policy. By collaborating, in this case, sharing the learning experience, the agents would have a more prompt and accurate understanding of the conditions, thus, using significantly lower time to learn the route-to-exit than the agents without collaboration. In the scenario of the simple environment, agents' performance reached a steady state at around 5000 episodes, and agent steady-state performance is better than that in the complex environment, which is expected, as the learning in the complex environment is much more difficult. The episodes needed to reach a steady state also showed the level of complexity of the environment. The number needed to learn can be used as a learning time limit for planning and resource assignments. In the real-life evacuation situation, the learning episodes could be translated to the number of agents required according to the size and complexity level of the area in the building.

One common problem using the RL algorithm is the convergence rate: the speed to converge or stabilize to a specifically targeted performance value. In this study, results obtained by adopting the multi-agent collaboration showed a higher convergence rate than the single-agent method results, as demonstrated in both studies, which is another advantage of utilizing agent collaboration. It is evident from the results that, the multi-

agent collaboration method can find an explicit and steady optimal route solution faster and easier.

The use of autonomous agents for exploration could save time and minimize the risk for human beings. The agents can provide a generic outline before the exploration is finished. As the exploration process goes on, a more detailed evacuation route will be suggested. The information, including a holistic view of the map, relative location of the evacuee, and available evacuation route, can be manifested through mobile devices or available digital displays. The information detected by the robot agents can also be transmitted to first responders, like police, firefighters, etc., who need to enter the buildings of the transportation system. For airport certificate holders, this kind of assistance can be amended to the airport emergency plan as a part of their airport certification manual to comply with Title 14 CFR, Part 139.

In the scenario of the simple environment, agents' performance reached a steady state at around 2000 episodes, and an agent steady-state performance is better than that in the complex environment, which is expected, as the learning in the complex environment is much more difficult. The episodes needed to reach a steady state also showed the level of complexity of the environment. The number needed to learn can be used as a learning time limit for planning and resource assignments. In the real-life evacuation situation, the learning episodes and death counts could be translated to the number of agents required according to the size and complexity level of the area in the building.

The benefit of the multi-agent collaboration was further confirmed by the second study, where the threats were moving at either a pre-defined route or randomly, on top of the complexity of the environment, as well as the experiment from a more complicated

airport environment. The communication and sharing of information helped agents to focus on the most likely optimal routes without the need to explore all the possibilities of the evacuation routes. This is certainly demonstrated by the faster convergence rate of the agent's rewards plot. Although the final rewards were similar between the no-collaboration and collaborative agents, the saving the convergence times implies that the collaborating agents can find the optimal routes faster, which implies time saving the evacuation situations. Because in an emergency every second count, this savings in time could translate into lives saved with faster evacuation.

It has been recognized that one common problem using the RL algorithm is the convergence rate: the speed to converge or stabilize to a specifically targeted performance value. In this study, results gathered by adopting the multi-agent collaboration showed a higher convergence rate than the single-agent method results, which is another benefit of using agent collaboration. It is apparent from the results that the multi-agent collaboration method can find a clear and steady optimal route solution quicker and easier.

One limitation of this study was that the experiment environment was fully observable even though unknown to the agents in the beginning. The agent can't fully observe the environment in certain circumstances, which means the holistic map is unavailable. Under this situation, it is necessary to introduce the partially observable Markov decision process (POMDP). In POMDP, it is assumed that the system dynamics have the Markov property, but the agent cannot observe the underlying state directly. In ordinary Q-learning, when the state and action space are low-dimensional and discrete, the Q-Table could be used to store the Q value of each state-action pair. When the state

and action space are high-dimensional and continuous, it is challenging to use the Q-table to track state-action values. Under this circumstance, it is more effective to transform the Q-table update into a function-fitting problem. And to be specific, in our experiment environment, the obstacle is moving in a fixed trajectory. However, in the real-life setting, the threats are probably moving in a random trajectory which is hard to predict. So, this phenomenon will significantly increase the complexity of the circumstances.

During this experiment, we observed that some agents fell into a deadlock (endless loops) due to the combined effect of exploration and exploitation. In some situations, the exploration rate decreased before the best actions in the current state had been learned. The agents may thus not take the optimal action or even fall into a deadlock loop, which will make the reward for that episode extremely low.

The size of the room is limited to 10*10 or 10*20 meters in both studies. For agents with collaboration, the possibility of agents touching the threats would be decreased to zero after specific trials, but death counts still exist after a long period of learning. Even the death counts could stabilize to a low value for the agent without collaboration. For a bigger-size environment, this could be a severe problem. As the interaction effects between the complexity and the collaboration method were significant, the collaboration method will have much better performance in a more complicated environment. In a real-life emergency evacuation, the actual area of the evacuation would be much bigger and more complex. The collaboration method will thus be much more beneficial to save the resources and the time for the evacuation process.

Conclusions

Agent exploration can be an excellent substitute for human exploration in a dangerous environment during evacuation. The use of agent exploration can generate a digital map with the optimal route in the mobile app, which would reduce the time for evacuees to find the exits. A multi-agent collaboration method is an approach that lets agents find exits faster with lower risks. The agents showed better performance in discovering time, death counts, and rewards. There were significant interactions between the complexity of the environments and the collaboration method on discovering time, death counts, and rewards. It is timesaving in the emergency evacuation to use the agents to complete the tasks and use multi-agent collaboration to find the optimal evacuation route. It could further reduce the time and threat of the tasks.

Recommendations

For future research, a better exploration and exploitation strategy can produce a higher performance in evacuation efficiency. The fixed environment can also be changed to a stochastic and dynamic environment. A more complex stochastic environment can cause a much lower convergence rate for the algorithm. Deep RL and partially observable Markov decision process would be suggested for solving this problem in a future experiment. A deep neural network has a good effect on extracting complex features. Combining deep learning with reinforcement learning may be an excellent solution for better performance in a complicated environment.

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