

An Investigation of Graph Neural Networks and Reinforcement Learning for Path Planning

by Jiaxin Zhong

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Prifysgol Cymru
Y Drindod Dewi Sant
University of Wales
Trinity Saint David

University of Wales Trinity Saint David

School of Computing

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Abstract

Artificial intelligence techniques have been successfully applied to many areas and shown promise results. Path planning is an essential task in many areas like robotics, autonomous vehicle and video games. Traditional path planning methods have been effectively applied for static environment (global path planning) but shown limitations in the performance of dynamic environment (local path planning). Most path planning tasks used data represented in graph structure. Graph neural networks (GNNs) can efficiently discover the information in graph structure data. GNNs are usually applied to task like image classification, natural language process. In this proposal, a novel approach that use GNNs techniques in path planning is investigated and analyzed. In addition, reinforcement learning can improve the agent action by a reward mechanism. Therefore, RL algorithms are applied to the process of path generation to improve the effectiveness and accuracy. The innovation parts of this study are that turn an optimal path searching task into a classification task and introduced feedback mechanism to enhance the performance of path generation algorithm.

1. Introduction

Path planning plays a significant role in navigational control engineering. Especially in autonomous mobile vehicle and robot. [1] It involves searching a path from a start configuration to the end configuration without collision. Many methods have been introduced to deal with this task. Classic approaches like divide and conquer method, virtual impedance method have shown promise outcomes. Artificial intelligence algorithms, such as neural network algorithm and fuzzy logic technique, also have been applied and showed high performances for path planning. The challenge and difficult part in path planning is dealing with dynamic environments with obstacles.

In this proposal, graph neural network and reinforcement learning are introduced to apply for path planning as an experiment to find a novel approach that improve the efficiency and accuracy compare to traditional path planning algorithms. The novel idea of this study is that turn a path planning problem from searching an optimal or suboptimal path to a classification tasks. Therefore, reduce the time of path searching and decrease the scale of computational expensive issues in path planning. Meanwhile, Reinforcement Learning is applied to boost the effectiveness of the path generation process.

1.1 Background

This section will briefly introduce the basic ideas and background of path planning, graph neural network and reinforcement learning. It would not include detail principles but just

give some fundamental concepts and applications about all these three areas.

1.1.1 Path Planning

In recent years, some areas like autonomous vehicles, drone, unmanned van, robotics have become more and more important to human life. Path planning is a critical problem that has to be resolved in those areas. The quality of path planning technique not only affect the efficiency but also related to safety.

Path planning is an algorithm that plan a path from one position to another position. Measurements of the algorithm can be varied in different areas. Shortest, cost, efficiency are some common performance criteria. In general, path planning has two types: local path planning and global path planning. These two classes also referred as offline path planning and online path planning respectively. Local path planning (offline) works on static environments which the all the information of the environment is fixed and can be accessed before planning. On the other hand, global path planning (online) works on dynamic environments. [2] Finding an optimal or suboptimal path from the initial state to the target state could be addressed as a NP problem.

1.1.2 Graph Neural Network

Graph is a powerful tool that can present most of the problems in our nature. In many ways, it is elegant that describe the data we receive from both reality and virtual worlds by using graph structures. For examples, social networks and transportation networks. After use graphs to present and describe the problems, handling the graphs to solve the problem become the next concern.

Graph Neural Network (GNNs) have become a prominent learning structure of graph. It can be applied to tasks like recommender systems, natural language processing and images. [3] Most GNNs use a mechanism call message-passing that merge local neighbor's information to build node representation. This allows the network to reason about the relationships between nodes and edges, and to make predictions or classifications based on this information. There are many different architectures and variations of GNNs, each with their own strengths and weaknesses. Some of the most common GNN architectures include graph convolutional networks (GCNs), graph attention networks (GATs), and graph recurrent neural networks (GRNNs).

There are still some challenges in GNNs, [3] like overfitting, scalability, representation bias and lack of interpretability. One challenge which highly related to this study is that GNNs are typically designed to work with static graph and not good at working with dynamic graph which important to this study.

1.1.3 Reinforcement Learning

One of the essential purposes of artificial intelligence (AI) is to build an autonomous agent that can actually act and deal with the environment by itself like human. Machine learning is an important field of AI that have significant development and are improving the state-of-art in tasks like data analysis, image recognition and natural language processing. Machine learning can be categorized as three classes: supervised, unsupervised and reinforcement learning. [4]

The basic concept of Reinforcement Learning (RL) is learning through interaction. With a reward mechanism, an agent interacts with the environment and alter its behavior according to the reward feedback. It was inspired by the behaviorist psychology that reward credit when you make a good move and punish when you make a mistake while training. RL has been successfully applied in a wide range of applications, including game playing, robotics, and recommendation systems. One of the key advantages of RL is its ability to learn from experience, which makes it well-suited to problems where the optimal solution is not known in advance or is too complex to be explicitly programmed. [5]

1.2 Purpose of the Study

This study aims to apply two machine learning techniques, graph neural network and reinforcement learning, to find an efficient and accurate approach for path planning in dynamic environments. The purpose of the study is to investigate how these advance machine learning algorithms can be applied to work on path planning and how much this approach can improve the performance of global path planning. Understanding and the abilities to apply artificial intelligence algorithms are also part of the outcome of this study.

1.3 Scope and Limitation

The scope of this study includes several aspects. First, theoretical research into path planning, graph neural network and reinforcement learning. Second, applications of path planning, graph neural network and reinforcement learning. Third, approaches have been applied to improve the performance of path planning and the advantages and disadvantages of each approach. Fourth, develop a new algorithm and technique for using graph neural network in path planning, including training methods, optimization techniques, and integrate reinforcement learning as a feedback mechanism to improve the path searching.

There are several limitations in this study needed to be consider:

1. Data requirements. Graph neural networks require large amount of training data. Lack of suitable data to training and test models may result in poor performance.
2. Complexity. Graph neural networks and reinforcement learning algorithms can be

difficult and highly complex to train, both require significant computational resources which are limit in this study.

3. Model Structure. Lack of deep understanding and application experience of graph neural network and reinforcement learning may lead into create an ineffective model.

All limitations listed above should be carefully handled during the process of experiment.

2. Literature Review

In this section, some of the development of path planning, graph neural network, reinforcement learning will be reviewed. Each of these techniques has thrilling progress and applied to many situations. Due to the purposes of this study and the space limitation of this proposal, this literature review would only cover researches and papers that are significant or related to this study.

2.1 Path Planning

Path planning is a process of finding an optimal path from a start configuration to another configuration. It has become an essential task in many important areas like autonomous vehicle, robotic, video game. Many approaches and algorithms have been developed and improved after all these years application. Traditional algorithms like Dijkstra's algorithm, A* algorithm, and the D* algorithm are very common and popular algorithms even in these days. They are efficient for small and simple environments but can become computationally expensive for larger and more complex environment. Path planning methods can be categorized as two main classes: classic methods and artificial intelligence methods. [2]

Grid based method uses a grid on configuration and represent each configuration as a point in the grid. Objects are allowed to move at every point to nearby lattices. The strategy is similar to A* algorithms searching activity to find a path from the start point to the end point. The quality of focuses on the searching path through all the grid makes it unsuitable to apply to high-dimensional issues. Markus Schutz et al. [6] proposed an approach to inject free space data into the grid matrices improves the following path searching and shape estimation in the following calculation of the box model. It is useful to help alleviate the effect because of the division as well as affiliation error. As grid-based method cannot performed well in high dimensional spaces, rapidly exploring random tree method was introduced. It constructs incrementally that rapidly decreases the estimated differences of a random chosed point to the tree. Rapidly exploring random tree has been accepted for planning a path in navigational tasks that contain varied constrains and obstacles.

Virtual impedance method introduced to enhance the path smoothness. It improved the objective execution in both dynamic and static conditions by setting portable impediments. Impedance control strategy is applied for crash shirking calculation by changing over the

separation of the object and impediment to a virtual power dismissing object from snag. [7]

Divide and conquer is a famous algorithm in computer science. It also has been applied successfully in path planning. In order to simplify the search, condense the search area and job of defining fitness function has been introduced, in that case, divide and conquer have been adopted to solve problems by develop a separate behavioral module which can search and plan the path individually using an evolutionary algorithm. Nagabhushan et al. [8] have given a procedure established on quadtree method for development of the smallest path from a given goal position to any given target position.

As the massive techniques emerge in artificial intelligence area, there are also some artificial intelligence approaches, or so-called heuristic methods, have been proposed for path planning.

The idea of neural network was inspired by the biological human brain. The main idea of this technique is that structure model with layer of neurons that are fully connected to the next layer. Each neuron has different weight and can scale the proportions of the input features. A back propagation mechanism was introduced to update each neuron weight according to the feedback of the output layer in each iteration. Utilizing the neural network about the connection of nearby neuron to describe the arrangement space of the environment to improve the generation of path has shown positive outcome. Furthermore, improved the path planning process by the association of every neuron and its local information. Lebedev et al. [9] proposed an approach called dynamic wave expansion (DWENN) is a novel technique that is utilized by play out the path generation which required no precedent data of the environment and also no learning procedure.

2.2 Graph Neural Network

Since graphs have a strong ability to better describe the connection of phenomenon and problems in our daily lives, techniques that can discover the patent and information have development rapidly in the last decades. Building artificial intelligence models that dealing with data on the graph are called graph neural networks, or in short GNNs. [3]

Gilmer et al. [11] provided a mechanism call message-passing (MP) mechanism which construct nodes by aggregating local nearby information to represent data. Most of the GNNs model based on this mechanism, such as Defferrard et al. [12] proposed a model by adding a convolutional filter on graph with fast localized spectral filtering technique to learn features on graphs more efficiently. Bresson and Laurent [13] test different architectures like LSTM and ConvNet to graphs with arbitrary size. As a result, they found that ConvNet performed better than other architectures. Furthermore, most effective ConvNet used gated edges and residuality techniques which plays an important role in multi-layer architectures. Those approaches that used MP mechanism also called MP-GNNs. This class of GNNs is basic structural which means that the node representation only depends on the local information of the graph. [10]

Several techniques have been developed in order to alleviate this limitation. Such as (i) stacking multiple layers [13] which can transfer information from one node to several layers, therefore distinguish the representation of different two nodes that far-away from each other. Nevertheless, this approach can be insufficient for long-distance nodes due to over-squashing phenomenon. [14] Another technique (ii) applying higher-order GNNs to calculate node-tuple aggregations. [15] [16] Though these two approaches can be computationally expensive to scale compare to MP-GNNs.

For arbitrary graphs, its lack of canonical positional information of the nodes which limit the representation ability of GNNs to identify the symmetries of graph and isomorphic nodes. In order to tackle this issue, positional encoding (PE) of the nodes was introduced. Dwivedi et al. [10] proposed a novel approach call LSPE (Learnable Structural and Positional Encoding) which alleviate the affect of this issue by aggregate instances of sparse GNNs and fully-connected Transformers-based GNNs. Their experiments shown performances which surpass the state-of-art of that time on three datasets. In addition, their evaluation found that MP-GNNs can be outperforming fully-connected GNNs, therefore suggesting a potential to develop a highly efficient and powerful structure for graph.

Convolutional Graph Neural Network is another important technique in GNN. Kipf and Welling [17] proposed a scalable approach for graph-structure data by using an efficient variant of convolutional neural network. They used hidden layers to represent the information and features of nodes which result in outperformed related method at that time. Based on Kipf and Welling's model, Wu et al. [18] proposed an approach called the simplified graph convolution model which decreased the complexity by removing nonlinearities and collapsing weight matrices between continuous layers. Veličković et al. introduced a graph attention networks (GATs) which can transfer information from one node to specifically different nodes in its neighbors without intensive computation.

Given a GNN layer, tasks over a graph can be classified as three kinds[3]: First, node classification. In that case, tasks are aim to predict target for each node and the output is equivariant. A good example is classifying protein functions in a given protein-protein interaction network. [19] Second kind is graph classification. These tasks aim at searching information through the entire graph and the output is invariant such as classifying molecules for their quantum-chemical properties. [20] Third, link prediction which we might interesting in information of the edges or predicting if an edge is exist. Example like predicting links between drugs and diseases—drug repurposing [21].

GNNs without graphs are related to deep sets and transformers which are a very powerful techniques in machine learning areas. Task like natural language process can hardly represent in a graph structure. Therefore, it requires GNNs to perform without a graph, that is when transformer is all that it needs. Another reason is that transformer can enhance the ability of using hardware capacities of GPU and CPU.

2.3 Reinforcement Learning

Artificial intelligence can be classified as three categories: supervised, unsupervised and reinforcement learning. One of the most important goals of AI is to develop an agent that can learn and react by itself like human being. Reinforcement learning aims to build an agent that improve its action by the feedback mechanism in each iteration. Reinforcement learning construct by an experience-driven autonomous learning framework. [4] It was first introduced by Barto et al. [22] and Sutton [23], the interest in RL has increased dramatically since then. Watkins' proposed Q-learning approach which become a popular technique in RL. It used a delayed reward mechanism to regularize the action of the agent by learning from totally unknown environments. It also has been successfully applied to many areas. The balance between exploration and exploitation presents one of the primary challenges in Reinforcement Learning.

Generally, there are two fundamental tasks in RL. One is policy evaluation which calculates the cost or value function according to the set policy. Another one is policy improvement which evaluates the obtained value and improved the policy. Algorithms to perform these two steps are called Policy Iteration (PI) [24] and Value Iteration (VI). PI and VI are using to search an optimal solution by iterate perform policy evaluation and policy improvement. In this proposal would use PI as a main feedback design mechanism.

RL algorithms have been mainly used to find an optimal regulation or track behavior in two kinds of systems: 1) single agent system; 2) multi-agent system. The goal of optimal regulation is to build a controller to make sure the outcomes of the systems can converge to zero or close to zero. [5] In this proposal, designed model would be a single agent model which monitor and regularize the action of path generation iteration.

RL algorithms have two classes of learning control method in optimal problems, that are on-policy and off-policy. [25] The former method assesses or upgrades the same policy as the one that makes the decisions. On the other hand, off-policy uses two separated functions. One function called behavior policy is used to generate data and the other function evaluate and improved called estimation policy or target policy. [5] Off-policy often shows more efficient and fast since it reused the experiences from the executing a behavior policy. Moreover, off-policy algorithms consider the probe of noise to explore more information.

3. Research Methodology

In this section, the basic principles of the designed model are introduced in detail. There are theoretical and mathematical concepts about these areas in this study. This research involves three steps process to build a model that can efficiently finish a path planning task

given an environment and two configurations. Both optimal path or suboptimal path can be accepted in this study.

3.1 Experiment Design

3.1.1 Model Structure

The system structured in three parts. First, an algorithm to generate path given a grid and two configurations. The second part is to train an artificial intelligence GNNs model that can classify a given path into an optimal path or not. The third part is utilize Reinforcement Learning to improve the process of path generation. The process of path searching would also be the process of reinforcement model learning. On the other hand, the training of GNNs model would be an independent task.

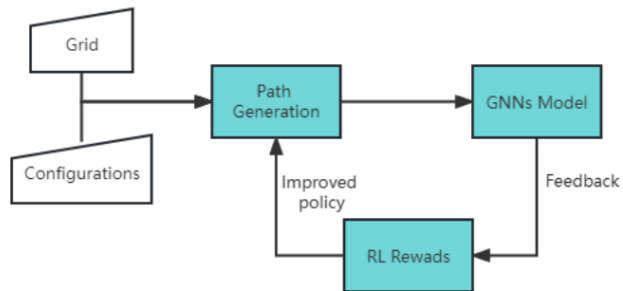


Fig 1 Model Structure

The input of this model: 1) an environment represented as a grid; 2) two configurations that represented as two points in the grid. One is the start point and another is the end point (target configuration).

The outcome of this model: an optimal path or suboptimal path from the start configuration to the target configuration.

The procedure of the program: input a grid and two configurations to the path generation algorithm, each generated path then be passed to the GNNs model and then would be classified as an optimal path or not in degree. Repeat this process until a goal path is found. Reinforcement learning would regular the action of path generation algorithm in each iteration after a path has been given a degree that suggest how close this path to the target path.

3.1.2 Path Generation

There are many path generation algorithms in path planning. Most of them are described in section 2 literature review. Rapidly Exploring Random Tree (RRT) Method is partly adapted in this study, but only used it to generate path without the part of outcome evaluation in this method. The RRT algorithm builds a tree rooted at the starting configuration, and iteratively extends the tree towards the goal configuration using random samples from the search space. In each iteration, a new configuration is randomly generated and added to the tree by connecting it to the nearest existing configuration

3.1.3 GNNs Classification Model

Since path generation is used a graph representation, grid-based GNNs is used in this experiment. Different from traditional GNNs that used to discover the information on the graph. Here dataset is a set of tuples that contain a grid and two configurations and a path with a label that addresses if the path is an optimal path or not. The training process involves a cost function that consider both the cost and distance on the graph. The trained GNN model would be able to classify a path as optimal path or not given a grid and two configurations. Finally, the performance of the grid-based GNN model is evaluated and tested to determine its effectiveness in solving path planning problems

3.1.4 RL Feedback Mechanism

Reinforcement Learning involves several key steps to develop an effective decision-making solution. Q-Learning is adapted in this proposal. Firstly, an environment is defined that consists of a set of states, action (Path generation) and rewards. The agent in here is the path generation algorithm. Each iteration agent can learn by rewards until the optimal policy is found. Once the RL algorithm has learned the optimal policy, the performance of the agent is evaluated and tested to determine its effectiveness. This involves measuring the agent's ability to achieve its objectives under varying conditions.

3.2 Research Strategies

3.2.1 Literature Review

Literature reviews has been conducted into three different areas as path planning, graph neural network and reinforcement learning. The purposes of these reviews are to understand the development of all these three areas and estimate the usability of the proposed model. Furthermore, understood the advantages and limitations of each approach can better help to choose the suitable method which will applied in this study.

3.2.2 Software Environments

This study would mainly focus on software development. The emulation of a real environment would be conducted in MATLAB; the path generation algorithm, reinforcement learning and the GNNs model would be constructed in PYCHARM using python; scikit-learn is a very powerful and effect tool to develop artificial intelligence model. So, scikit-learn libraries would be used to train GNNs model and assemble RL techniques into the path generation process. Tensorflow and Panda would be used to handle the data structure and some other basic operation of files.

3.3 Resources

Access to information resources will be needed through the whole process from proposal to experiment. Basic research engine like google scholar, google search would be used to search papers, journal and so on; tutorials from YouTube; experience from forums.

A computer with a high computational ability GPU and CPU is needed for the computation of artificial intelligence techniques. Some software and python framework needed to be installed like PYCHARM, tensorflow, scikit-learn, panda. Basic Microsoft Offices will help to collect data and information. MATLAB will be used to simulate the grid and agent movements. A cluster of computers can accelerate the process of model training and the process of path planning.

Experts in those areas can help to build a more effective and efficient model in that case.

3.4 Timeline

The initial planning of this project started from April 2023. Some preparation like information searching, feasibility analysis and professional knowledge learning would be done before May. Note that steps mention above might repeat again anytime during the experiment. Pseudo codes are on progress for the basic model structure. The final project is expected to be finished before the end of this September. More details timeline are shown in Fig 2.

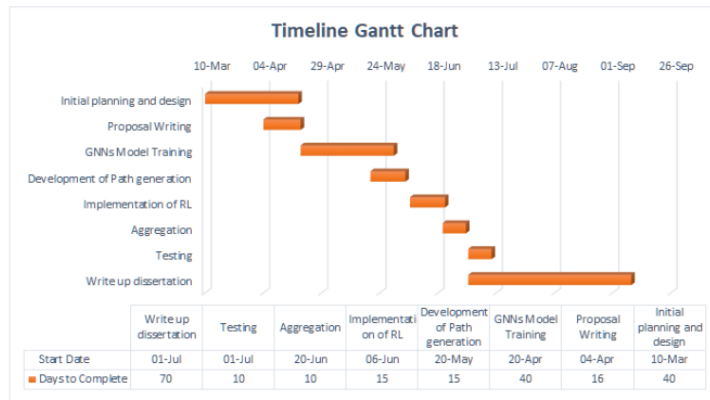


Fig 2 Project Timeline

4. Expected Result

The expected result of this proposal is to build a system that can efficiently complete a path planning task given a grid and two configurations without computational expensive problems. Although the ideal goal would be searching for the optimal path that is the best in the condition estimation criteria such as shortest, minimum cost. The calculation of path generation should be fast enough to meet the requirement of autonomous control system in order to apply to autonomous driving or unmanned vehicles. The matrices of grid should be able to describe additional information of the environment like cost, distance, obstacles. Furthermore, this system should be able to handle dynamic environment which means it can apply for both global path planning and local path planning.

The experimental data should be record in files during the development process in details. It would be best that can visualize the process of path generation and each iteration results. At the end, a dissertation about the detail of this study would be complete after the outcome of this experiment. A tutorial of how to use the system is also needed for the reader to try the system.

In conclusion, this novel approach is aim at improving the effectiveness and accuracy of the path planning task compare to traditional approaches and provide insight into the application of GNNs and RL algorithms.

5. Evaluation

In this section, the formation of the data that used to train the GNNs model will be introduced. Meanwhile, the measurement to estimate the process of path generation and final system is specified in next chapter. As a review, there are some thinking into future work.

5.1 Data

There are several kinds of data that can use to train a GNNs model. Such as graph data that use a grid to represent the environment. The nodes represent a location and the edge can describe the relationship between two nodes; Sensor data that collected by various sensor like camaras, LIDAR or GPS; Trajectory data which obtained from real-world experiments or simulation and can represented as sequence of node or edge labels; Simulation data can be generated using MATLAB or physics engine can be an alteration dataset in the absence of real-world data.

In this study, graph data, trajectory data and simulation data would be more suitable to train the GNNs model and use them to test the system.

5.2 Measurements

In order to better understand and describe the performance of the system, some criteria are adopted in this experiment during different periods.

5.2.1 Training of the GNNs Model

Confusion matrix is a standard tool used to evaluate the performance of an artificial intelligence model. A confusion matrix is a table that shows the performance of a classification model by comparing predicted and actual values. Accuracy is another important measurement of the AI model. Time consummation would not be a main issue in the process of training GNNs model in this experiment as long as it is in an acceptable range.

5.2.2 Path Planning

Execution time would be the main concern in path planning system. Success rate would be used to describe how many times it takes to generate an optimal or suboptimal path. Meanwhile, the effectiveness compare to baseline of path planning should be consider in the end of the experiment.

5.3 Future work

Some potential future work include: 1) Improved the learning algorithm for both GNNs and RL which can better optimize the path planning process. 2) Multi-agent path planning. In this experiment, only use single agent to explore the grid and generate path, use multi-agent can boost the process of path generation. 3) Real-world implementation and testing. Since this experiment is based on simulation data mostly, therefore, it would be better to apply it to a real-world situation and test its feasibility.

6. Conclusion

This proposal investigates the idea of path planning using GNNs and RL. First, a basic literature reviews of path planning, GNNs, and RL have been reviewed at the beginning. Path planning is an important task for areas like robots, autonomous vehicle, unmanned van and video game. GNNs is a thriving artificial intelligence area which can discover useful information from grid structure data. RL focus on creating a self-learning agent in a unknown environments. The combination of these three techniques forms a novel approach in this proposal.

The basic ideas and the choices of each technique are described in section 3 methodology. There are a lot of different method to apply GNNs and RL. For GNNs, this proposal decides to use message passing mechanism and node embedding techniques. Q-Learning is a powerful and popular method for RL implementation. Path generation method can use rapidly exploring random tree algorithm. The feasibility of each chosen methods is still needed to be tested in future experiments.

Furthermore, the methods of expected results are specified and the evaluation standards are described in this proposal. In short, the outcome of the experiment is an effete and robust path planning system compare to traditional path planning methods.

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An Investigation of Graph Neural Networks and Reinforcement Learning for Path Planning

GRADEMARK REPORT

FINAL GRADE

GENERAL COMMENTS

Instructor

71 /100

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JIAXIN ZHONG

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ENGAGEMENT WITH LITERATURE

(20 marks)

-  Fair attempt is made in terms of conveying the importance of graphical neural networks and its applications to path planning.

15

KNOWLEDGE AND UNDERSTANDING

(20 marks)

-  Path planning is introduced and its prior usage in the area of vehicular logistics is expounded on very well. For the dissertation phase you will need to extend your literature review to also consider path planning in the areas of logistics and supply chain management as this will aid you in terms of demonstrating its suitability across disciplinary domains.

15

COGNITIVE/ INTELLECTUAL SKILL

(30 marks)

-  Evaluation of associated planning algorithms does demonstrate an ability to critically evaluate included literature and in connecting inferred research aims to project scope.

16

PRACTICAL/ APPLICATION SKILLS

(10 marks)

-  Experimental design provided is valid though lacking its connections to an overall research methods based approach. No actual planning of project and or management of key tasks is listed within proposal. In so doing, timeliness of perceived delivery of and an ability to address unforeseen project overshoots cannot be addressed in full.

12

TRANSFERRABLE SFL/ PP

(20 marks)



Content layout is essentially fine and ideas are conveyed clearly (there are minor grammar errors).

13