Artificial Intelligence in Autonomous Motion Planning of Robotic Systems

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TABLE OF CONTENTS

ABSTRACT

As robotic systems are evolving and are getting more sophisticated, the expectations from these systems to complete complex tasks with a high success rate keeps on increasing gradually.

Motion Planning refers to the capability of a system to calculate the most optimal path to the destination after understanding the environment variables and tackling various emergency situations in the travel.

Motion planning of Systems are becoming more complex and difficult to control. Motion planning is being studied from the 1960's with various different approaches of kinematics, control systems, intelligent algorithms, etc.

Motion planning is being used in various different domains like underwater robotic manipulation, self-driving cars, Aerial vehicles, Defence purposes, etc.

Thus, extensive research is going on to improve the success rate of motion planning with minimal costs with the help of artificial intelligence models like the different variants of the RRT models, RANSAC Algorithm, Reinforcement learning based models, POMDPs, etc.

In this literature study report, we will discuss about various different research going on in the exploration of different path planning models for a variety of tasks.

INTRODUCTION

Motion planning is a branch of computer science and robotics which has been studied from last four decades mainly from a kinematics point of view for robots with limited abilities. It involves the travelling of the robotic system or part from start point to the destination point in the most efficient way possible. Here, we will discuss some basic terminologies about motion planning and related processes.

A path is a sequence of various configurations or positions which can guide the robotics system from its starting node to the goal node. The term Path Planning refers to the search of a path with no obstruction with any obstacle in the workspace.

A Trajectory is an expression of the robotic part's position as a function of time. Therefore, Trajectory planning is the planning of motions of a robotic part with respect to time. Motion planning generally refers to path planning or Trajectory planning depending on the application of the robotic System.

COLLISION DETECTION

Collision Detection is a very crucial part of Motion planning as the planner should guarantee that no collisions occur, otherwise the system will fail to function properly due to crashing of the robotic hardware. There are two types of collision avoidances: Local Collision Avoidance and Global Collision Avoidance.

Local Collision Avoidance occurs when the environment is unpredictable and there is no or poor prior knowledge of the robotic environment. This type of Collision avoidance requires continuous feedback control so as to notify the robot on the occurrence of an obstacle or an emergency situation.

Global Collision Avoidance is the planning of a collision free path before the start of the following of the path by the robot. This is possible when there is adequate knowledge about the robot's environment. The robotic environment has to be plotted on a flowmap and it should be ensured that the path/trajectory traced has no collision with any type of obstacles.

The Configuration Space refers to the physical space the robotic system and all the obstacles exist in. A configuration of the robot is the set of all the parameters defining every point of the robotics system or the object in the configuration space. The obstacles for the robot are to defined along with their configuration for avoiding them in the path planning.

TAXONOMY OF MOTION PLANNING PROBLEMS

There is a commonly used taxonomy to describe the four major divisions of a general Motion Planning Problem – **WRIT**

W – Workspace

R – Robot

I – Information

T – Task

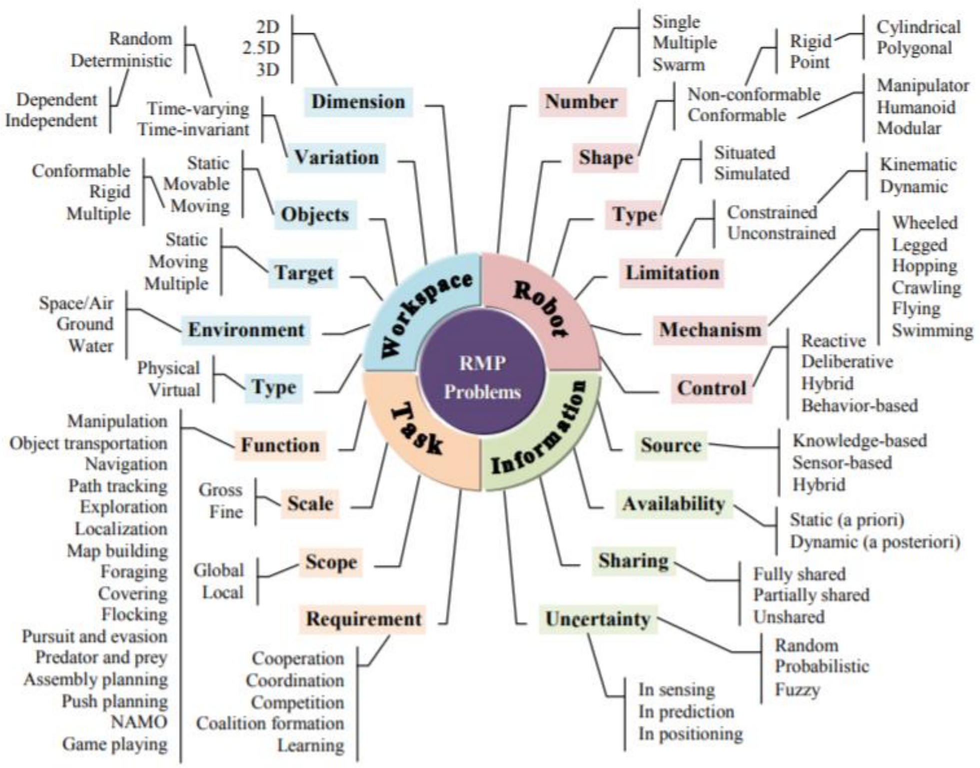

Fig.1 The Workspace–Robot–Information–Task (WRIT) taxonomy for robot motion planning problems.

Workspace – The Workspace Division involves the determination of the various objects in the configuration space, the coordinates of the start and goal node of the robot, static or dynamic objects information, size of the obstacle and coordinates of each point of the obstacle/ object , etc.

Robot - The Robot Division involves all the constraints the robotic system has, the type of locomotion it can do, number of robotic parts coordinating, type of control used to control the different parts of the robot, etc.

Information – The Information division deals with the various different important tasks like source of the information whether knowledge based or sensor based, availability is whether static or dynamic, about the uncertainity in sensing/ positioning/ prediction, etc.

Task – This division takes care of the main aim of the system, which part is to be used such as gripper/ welding gun/ etc. , function at a specific coordinate and a specific configuration of the robot either navigation or sensing, etc.

All these division work very closely with each other for optimal functioning of the robotic system and completion of the required task with maximum possible success rate.

Robotic Systems are used in very wide range of applications from underwater robotic manipulation for cleaning the water, controlling drones for accomplishing a certain task, development of self-driving cars, etc.

Each task has a different way of process and these processes use a lot of computation power and hardware resources which cost a lot.

For smart utilization of resources with minimal errors, we need to incorporate and research on various different algorithms in order to choose the most optimal technique to finish the required task.

From the last few decades, Robotics Engineers with the help of Artificial Intelligence have been doing extensive research on various different algorithms for different types of tasks and working on identifying best possible algorithms for the task needed.

In the literature study section below, we will discuss the studies of various different robotics and computer scientists working in various different application of robotic systems like ground robots, underwater robots, self-driving cars, etc.

LITERATURE SURVEY

This sections presents a discussion about the ongoing research in the area of Motion Planning in various sectors using the help of Artificial Intelligence.

1) G Farias et.al. (2018) implemented Neural Network based Obstacle Detection by fusing various proximity sensors. The automatic calibration by utilization of Artificial Neural Networks reduces the time taken in the calibration as compared to commonly used methods in which the obstacle detection models were normally non-linear functions which differ for each different type of sensor attached to the robot. This type of calibration the sensors also rules out the invariances about the characteristics of the obstacle like the colour, shape, texture, etc. which depend on sensor type (eg., infrared or ultrasonic) and like light intensity, etc. This method was experimented on the Khepera IV Robot in an indoor environment with an Indoor Positioning System (IPS) and the Braitenberg algorithm was selected for the position control with obstacle avoidance.

2) M Arslan et.al. (2017) implemented computer vision based and navigation algorithms for a mobile robot using Support Vector Machine (SVM) and A* methods. The NAO humanoid robot was used to implement the navigation and capture images of the world map. The images captured were classified into 2 different classes: regions with obstacles and regions without obstacles. The SVM method was used for this classification of regions. This knowledge of whether a specific region is obstacle free or not was depicted with the help of a map. The A* algorithm was then used for finding the near optimal path for the robot from the start point to the goal point on the map. This method allows in the navigation of the mobile robot where the commonly used sensors like the magnetometers, sonars, etc. do not work reliably and vision data can be totally relied on.

3) In Autonomous Underwater Vehicles (AUV), there is an increasing necessity for performing manipulation tasks with higher complexities. For being able to complete complex tasks accurately there needs to be complete motion co-ordination between the working arms and the mobile base especially when controlling and floating the AUV also come as challenges simultaneously. D Youakim et.al (2018) presented an approach to manipulator motion planning exploiting the loose coupling between the arms and the AUV. This approach is based on Multi Representation Multi Heuristic A* (MR-MHA*) and demonstrated how it develops efficient trajectories by the exploitation of decoupling. The quality of the developed trajectory was calculated in terms of the path length with maintaining relatively faster planning time. The framework was implemented on a real underwater mission simulation which was a success.

4) G Prabhakar et.al. (2017) established a deep learning system for on-road obstacle detection and classification method beneficial for self-driving cars perception purpose. The region-based convolutional neural network system (R-CNN) was trained with image datasets from PASCAL VOC for detecting and classifying on-road obstacles like vehicles, dividers, pedestrians, etc. They achieved a processing frame rate of 10 fps on the Titan X GPU for a VGA resolution image frame. The performance of the model could have been optimized by utilizing a wider neural network model such as the GoogleNet and an embedded GPU platform such as Jetson TX1. Further studies can be in the direction of improving the performance for Indian Road Scenario which can be tested by creating a dataset on Indian Road Vehicles.

5) J Berisha et.al. (2016) presented the application of Fuzzy Logic Controller (FLC) for the obstacle detection and navigation of robots by interpreting signals from 3 different sensors and defining the motion by giving 2 outputs as left and right motors as actuators. The robot on which the algorithm was implemented is 'RoboKos-II Pathfinder'. The C++ based algorithm was used on MATLAB's Fuzzy Logic Toolbox. Mathematical Modelling of the Robot was established for determining the position and velocity and acceleration data on the floormap. For optimal positioning of the robot on the map various deep learning approaches like the Kalman Filter (KF) and the Extended Kalman Filter (EKF) were applied. Implementation of fuzzy logic brings a certain amount of simplicity and is a good approach when there are high levels of uncertainties.

6) M Manchini et.al. (2017) implemented Deep Learning Neural Networks for robust and quick obstacle detection by training on real and synthetic images. This technique can be utilized in operations where the robot is travelling with extremely high speeds for e.g. Self-Driving Cars at higher speeds. The speed in the sensing was achieved by trading some depth accuracy for faster recognition of obstacles. They could establish detection of obstacles at very long range with high speed around 300 Hertz. The depth estimating algorithm was based on an Encoder-Decoder Convolutional Neural Network Architecture. The test was done on 2 type of inputs: normal monocular images and optical flow powered monocular images. The proposed algorithm was able to recognize obstacle's depth even though the beginning images captured may have been blur, blackened or corrupted in any other way. They plan on improving their study by obtaining a semantic knowledge of the scene by integrating the depth estimation with semantic segmentation algorithms along with fine-tuning on real images.

7) S Palanivel et.al. (2017) developed a Vision Based Obstacle Detection Model for detecting any large rocks/any other type of obstruction on Rail-tracks which can be bothersome for the rail travel. The method proposed includes a single thermal camera and the ADA Boost Classification Algorithm is used to detect any obstacles in the level crossing and calculating the distance the obstacle and the train head. This technology can serve as a Railway Safety Monitoring System which is most useful when there are natural disasters like landslides, Earthquakes, etc. This work can be extended for various environmental conditions like lighting, climates, etc. This implementation can progress with determining the severity of the obstacle therefore determining whether the obstacle can be removed from the rail-track or not.

8) L Chen et.al. (2017) proposed a method called LiDAR-Histogram which is based on the Lidar point cloud map called as Lidar-imagery. This efficient and organized map is made by transforming the unorganized 3D point cloud into a Lidar-specific 2D Coordinate System. This idea was implemented for on-road obstacle detection. The 3D traversable road plane in front of the vehicle can be projected on the 2D plane as a line segment. In this manner, the traversable road and obstacles are transformed into a simple linear classification model in 2D space. The RANSAC Algorithm was implemented to obtain the linear model of the road. The testing was done by implementing the algorithm on the off-road data collected by an autonomous driving vehicle and the KITTI-ROAD dataset.

9) L Chen et.al (2019) have proposed a modern motion planning model which learns from real time as well as artificial traffic scenarios from past experiences. This framework is named as ‘Parallel Planning’. This Deep planning method combines two methodologies in an end to end mode, Long Short Term Memory (LTSM) and Convolutional Neural Network (CNN). This model aims to reduce the error in the performance tremendously and make the planning model much more robust. In case of emergency scenarios, a hybrid model generated by the combination of a generative Adversarial Network (GAN) and a Variational Auto Encoder (VAE). This model learns to tackle such difficult situations by referring to artificial traffic situations and aims in decreasing the burden of heavy calculations during emergency situations. This model is mainly implemented on Autonomous Vehicles for learning real on-road situations and imitating a driving style of human drivers.

10) Abbas S et.al (2020) have proposed an end to end learning network for self driving cars which has the ability to perform joint perception along with prediction and motion planning. It also produces immediate interpretable representations for motion planning. The planning costs are consistent with the perception estimates which is difficult with the traditional methodology. They have implemented a representation which possesses properties like differentiable semantic occupancy and learning from human demonstrations. These features enable to carry on experiments with large datasets with scenarios with various challenges and closed loop simulations while following human driving behaviour. Their model could reduce the collision rate significantly and safer than various other state of the art planners.

11) AH Qureshi et.al (2016) have proposed a sampling based motion planning model for robotic environments which are complexly cluttered. They explored the algorithm called (RRT) Rapidly exploring Random Trees. A bidirectional version of the same RRT Algorithm was used known as Bidirectional Rapidly exploring Random Trees (B-RRT). They developed a new type of algorithm based on the B-RRT known as Intelligent Bidirectional Rapidly exploring Random Trees (IB-RRT*) which is highly useful in complexly cluttered environments. By comparing the proposed the new IB-RRT algorithm with its previous variations they came to the conclusions that the new proposed algorithm consumes lesser amount of memory for converging to the optimal planning solution with lesser number of iterations and has higher convergence rate compared to the older variants.

12) M Otte et.al (2015) presented the world's first sampling based asymptotically optimal path planning and re-planning algorithm for live navigation in dynamic backgrounds – RRT^x .Whenever an emergency situation like the encounter of a sudden obstacle with the help of various sensors, this algorithm rapidly updates the search graph and retraces the new optimal subtree which refers to the shortest path to destination node. This algorithm was compared to its counter-parts RRT^* and the $RRT^\#$ algorithms. The RRT^x algorithm inherits the characteristics like asymptomatic optimality and probabilistic completeness from RRT^* and the property of e-consistent graph maintenance for cost changes larger than e from $RRT^\#$. The analysis and experiments conducted described how RRT^x works extremely well in constantly changing backgrounds as well as static environments.

13) A Dobson (2017) proposed a sampling based scalable motion planning model for scenarios where there is collaboration of multiple robots. They proposed a method dRRT*, a variation of the previously existing dRRT model with new features like informed and asymptotically optimal. This method is made on the basis of development of roadmaps for each robot and searching for these structure's tensor product in the composite space implicitly. This model was first implemented on two disc-shaped robots moving among 2-dimensional polygons and then on a dual armed manipulator and then compared to the Implicit A* algorithm. While the Implicit A* fails for number of nodes greater than 500, dRRT* works with a success ratio of 100%. The dRRT* method avoids the necessity of the development of huge and dense roadmaps of many robots in the composite space making it more efficient in multi-robot motion planning where there are multiple simultaneous tasks to be implemented.

14) NT Dantam et.al (2018) have presented a task and motion planning framework (TMP) which is probabilistically complete, extensible and constraint based. The main ideology of this framework is leveraging incremental constraint calculation solving to optimally include all the geometrical data available at the task level. This incremental approach to constraint equation solving increases the precision of data given to the task planner from the motion planner, therefore improving the overall scalability of the framework. They have presented a new algorithm (IDTMP): Iteratively Deepened Task and Motion Planning. This IDTMP algorithm was tested on the Baxter Robot Manipulator to calculate the overall scalability in different situations with varied large numbers of objects and plans and the results show that this new algorithm improvised on the scalability to the object count and plan length compared to the previous manipulation frameworks. Their further research is in scaling this algorithm to handle with larger domains by caching and reusing plans and search trees.

15) Recovering the pose of an object among a crowd is an important task for efficient robotic manipulation but it is also a very difficult task because of severe clutters and occlusions. In such scenarios, when the observer fails to get a clear view of the object's orientation, the observer captures a new scenario from another point of view to improve the environment knowledge. J Sock et.al (2017) presented a multi-view active framework to learn about 6DOF pose of various object scenarios in a crowded situation. They used an Entropy based Next Best View Algorithm (NBV) which is used in complex scenarios where the movement of the robot is costly. The study showed that combining the multiple views of the object increases the object detection and pose estimation performance significantly irrespective of the base line and other complex scenarios.

16) JA Wolfe et.al (2010) have presented a hierarchical planning system for Robotic Manipulation which involves finding the kinematic solutions to the tasks and rake advantage of the information related to specific subtask irrelevance. The planning involves re-usage of the optimal solutions to the sub problems in the state abstracted search space. Future progress involves reducing the computation times for large tasks using extensions of State Abstracted Hierarchichal Task Network (SAHTN) algorithm which uses the available heuristic data and approximate models for guide searching and reducing the call to external solvers. Another possible improvement will be to utilize incremental adaptive search algorithms which can manage the trade-off between quality of planning and computation cost in a more efficient way.

17) Y Wang et.al (2020) have proposed an optimal Active Visual Search (AVS) policy of objects in indoor known backgrounds with an online setting. They modelled this type of problems as a (POMCP) Partially Observable Monte Carlo Planning which has been used in other benchmark scenarios with impressive results. This was the first time the POMCP method was used for Robotic Motion Planning Problem. The floor-map in the form of a two-dimensional grid map of the environment is the only requirement for solving AGS in small scenarios unlike other strategies which require expensive labelled data. They achieved a success rate of 0.76 with a path length 17.1 which is close to the state of the art but this works without any training. Further progress can be incorporation of object co-occurrence in the model of POMCP to further increases the performance of the planning.

18) A Akbari et.al (2019) proposed a combined heuristic based task and motion planning approach to solve bi-manual robotic manipulation problems. The method uses the FF heuristic state space task planner to take into account various geometric constraints though a variety of geometric reasoning procedures. The heuristic function can guide state space search to geometrically possible states. There is no need of geometric backtracking or any type of geometric precomputation. This model was tested with simulations as well as real life experiments and the results showed that the technique was efficient in terms of both success rate as well as planning time. Future progress in this method can involve the incorporation of semantic knowledge and planning methods like contingent planning which will enable flexibility in implementing this approach to scenarios involving manipulation of objects with varied constraints and attributes.

19) Z Pan et.al (2016) presented a new algorithm for collision free robot manipulator motion to pour liquid from one container to another. They presented a guided simulation and an optimization method to compute the liquid transferring trajectory automatically. Fluid motion is highly deformable for which they have used the accurate and complete Navier Stokes Model which provides the intricate information about the velocity distribution of the liquid body. The optimization based motion planning algorithm uses a heuristic approximation for guiding the manipulator because of the non-smooth and non-linear properties of liquid simulation software. The approximation based on energy does speed up the computation, but all the constraints are not completely met. The project becomes more complex when the number of particles used for the approximation of the fluid increases.

20) R Meyes et.al (2020) have proposed a Reinforcement Learning based, 6 Axis Industrial Robotic manipulator used for various production techniques like welding, gluing, cutting, etc. The RL algorithm used is cognition enhanced for complex motion planning with continuous trajectories. The model implements strategies by learning from previous experiences stored in a non-relational database which acts as a knowledge base for the agent. The learning algorithm is based on a modified version of the Q Learning Algorithm along with greedy exploration. The model was tested on a trained agent in a virtual environment first and then implemented on a real world setup. This model offers a wide range of production processes possible and the time, labour and lives at risk in such tasks can be significantly reduced. The more the experience the model gathers, better its precision will come out to be. So, further progress can be made by training the datasets with varied methods and testing the accuracy.

21) T Bandyopadhyay et.al (2013) proposed a new class of motion planning problems where the human intentions are unknown to the robotic system. The robot must identify the human behaviour and intentions and act accordingly and complete the specified tasks. They constructed a motion model for each human behaviour and then combined the models to a single (MOMDP) Mixed Observability Markov Decision Process. This model is a variant of the traditionally existing POMDP. The model was later modified for bringing the ability if changing tor adding new components in the intentions set. A new MOMDP solver, SARSOP was used for the implementation which assumed only discrete states. Further studies could involve the mixing of human intention states and implementation of contingent planning to learn from previous experiences.

22) G.E.Fainekos et.al (2005) formulated the problem of path planning in the form of temporal logics. Temporal logic not only expresses robot specifications such as avoiding obstacles or reaching a goal but also sequencing or temporal ordering of various different tasks of the robot. Considering the robot's environmental decomposition, discrete abstractions are first constructed. Using powerful checking tools, the discrete plans were generated which satisfy temporal logic. Finally, using hybrid control, these plans are translated into continuous trajectories. Further studies could involve to extend this approach to motion planning of multiple robots simultaneously and designing of a hybrid controller that guarantees the path formula's satisfaction with actuation and localization errors being present in the environment.

CONCLUSION

An important task in the development of autonomous robotic systems is to think of ways to give the robot the ability to make their own plans depending the situation it is facing. The basic process of Motion Planning refers to the planning of motion of the robotic part from the start node to the destination node in the presence of various uncertainties in the environment like obstacles, static or dynamic.

The incorporation of Artificial Intelligence in the part of recognizing the robot's environment efficiently along with obstacles and objects with their motion data has made the process of motion planning more efficient.

The introduction of Computer Vision in the motion planning process has boosted the task of object recognition with respect to the traditional Ultrasonic/ Infrared sensing.

Various Robotics and Computer Scientists around the globe are working on various path planning algorithms like RRT models, POMDP, Reinforcement Learning based Models, etc. which helps in comparing the efficiencies of these methods among each other and recognizing the most optimal technique for a specific task required.

Further research in this field will definitely help in improving the efficient working of robots in various tasks and in improving in human lifestyle in future.

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