A Review of Motion Planning Algorithms for Robotic Arm Systems

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Abstract. Motion planning plays a vital role in the field of robotics. This paper discusses the latest advancements in the research and development of various algorithms and approaches in motion planning in the past five years, with a strong focus on robotic arm systems. Sampling-based motion planning algorithms are prevailing and well-established methods. More effective algorithms such as optimization-based, Probabilistic Movement Primitives (ProMPs)-based and physics-based methods are feasible research directions to explore to improve the effectiveness. The evaluation benchmarking of the algorithm is a worthy research direction. The model-based methods can improve the efficiency of the task, but it has less ability to deal with accidents. In contrast, the model-freed methods can solve this problem, but it takes a long time to compute. This paper also provides an insight into robotic manipulation of rigid and non-rigid (deformable) objects. Based on the study, some challenges and future research trends are summarized, and some algorithms and approaches are suggested for efficient use of the robotic arms.

Keywords: Motion planning · Robotic arms · Model-based · Model-free · Deformable objects

1 Introduction

The development and wide application of robot technology have promoted the productivity of the country and the progress of the entire society. Robot technology can perform tasks that repeat work, such as welding, installation, and inspection. Even in dangerous environments, robots can work very well and even handle some unexpected situations. With the intensification of aging and the transformation of the market, robots are becoming more and more popular.

Among them, the robotic arm (manipulator) is one of the earliest robots used in realizing life and social production. There are many tasks that require the coordinated operation of two or more robotic arms, such as the task of lifting heavy objects or assembling mating parts. In the actual work process, the working environment of the robotic arm is very complicated, and there may be many obstacles outside. And when multiple robot arms need to complete a job at the same time, the mutual obstacle avoidance between the robot arms also needs to be considered. In order to ensure that the robot

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arm can work better and avoid obstacles effectively, it is of great significance to study the effectiveness of the robotic arm.

A collaborative robot refers to a robot that can directly interact with people in a collaborative area. Collaborative robots usually have the advantages of light weight, high safety, good adaptability to the environment, and strong human-computer interaction capabilities. It can meet the requirements of task diversity and environmental complexity. It is used to perform operation tasks that interact with unknown environments and humans and is an important development direction for next-generation robots. In order to achieve safe interaction and cooperation between robots and humans in different environments, it needs to have a lightweight mechanical ontology structure and a good motion planning algorithm.

In terms of the cooperative robot body structure, its driving joint generally uses a high torque density permanent magnet torque motor combined with a harmonic reducer transmission scheme to improve the robot's load/self-weight ratio, such as the lightweight type developed by the German Aerospace Center (DLR) Robot LWR and its commercial product iiwa robot [1] in cooperation with KUKA, the UR robot [2] from Universal Robots of Denmark, the Franka Emika robot [3] from Franka in Germany and so on. In recent years, human-computer interaction (HRI) has received continuous attention in academia and technology companies.

This paper discusses some advanced research on the issue of motion planning of robotic arm in recent years. Based on these studies, we present the latest advances and challenges in the robotic arm motion planning and sort out and integrate its methods and research projects. After analyzing and sorting out the research in recent years, some exclusive insights are summarized which are convenient for researchers to better understand the current research direction and results of motion planning of robotic arm system.

2 Search Strategy

The research problem of motion planning for robotic arm has been one of the prevailing topics in robotics and it attracts surges of endeavors to come out with plausible solutions to improve the performance and efficiency. This article mainly conducts literature review and research on some aspects of motion planning of robotic arm within the most recent 5 years. We searched for the relevant keywords from the four main academic searching engines such as Web of Science, IEEE, Scopus and Google Scholar. In this paper, our main search engine is IEEE, and our keywords include: Motion Planning, Model-Based/Model-Free approach and robot manipulation of rigid and non-rigid (deformable) objects. We researched the search results for the keyword "Robots Motion Planning" and chose the number of years since 2015.

According to the keyword "Robots Motion Planning" from 2015 till now, the search results in various search engines are as follows (Table 1):

Since the main search engine of this article is IEEE, the search results of IEEE under different years according to the keyword "Robots Motion Planning" are as follows (Table 2):

We can see from the table that Robots Motion Planning has been studied and valued increasingly by more and more researchers.

Table 1. Search results for Robots Motion Planning.

Search engine	Keywords	Years	Number of results
IEEE	Robots Motion Planning	2015-now	12396
Web of science	Robots Motion Planning	2015-now	3057
Scopus	Robots Motion Planning	2015-now	8458
Google scholar	Robots Motion Planning	2015-now	16200

Table 2. Search Robots Motion Planning in IEEE.

Search engine	Keywords	Year	Number of results
IEEE	Robots Motion Planning	2015	574
IEEE	Robots Motion Planning	2016	624
IEEE	Robots Motion Planning	2017	708
IEEE	Robots Motion Planning	2018	936
IEEE	Robots Motion Planning	2019	1006
IEEE	Robots Motion Planning	2020	297

3 Results

At present, the types of robots based on mechanical arms are mainly divided into single-arm robots, double-arm robots and humanoid robots. According to the needs of the task, these robots will respond accordingly through their robot operating systems, including controllers, motion planning, and environmental monitoring mechanisms.

3.1 Motion Planning

Motion planning is to insert a sequence of intermediate points for control between the given path endpoints to achieve smooth movement along the given path endpoints. Motion planning consists of path planning (space) and trajectory planning (time), as shown in Fig. 1:

The sequence point or curve connecting the starting point position and the end point position is called a path, and the strategy that constitutes the path is called path planning. Path planning is to find a series of path points to be used, path points are positions or joint angles in space. Trajectory planning is to give path time information. The goal of path planning is to make the distance between the path and the obstacle as far as possible

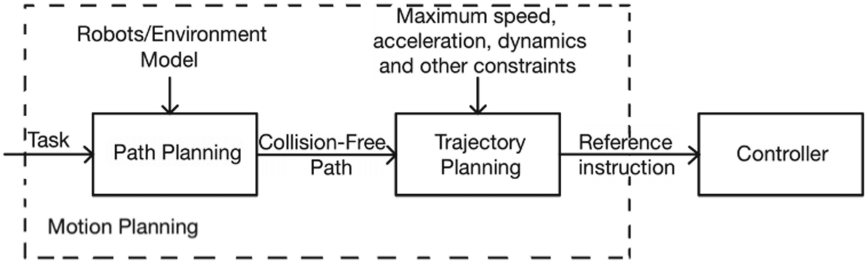

Fig. 1. Motion planning, path planning and trajectory planning

and the length of the path as short as possible, and the purpose of trajectory planning is mainly to make the running time of the robot as short as possible or the energy as small as possible in the movement of the robot joint space. We summarized the research on motion planning in recent years, as shown in the following Table 3:

The indoor path planning and motion planning methods based on POMDP was studied in [6], however, simulations were conducted rather than experiment with the actual robots. Although the LBT-RRT algorithm in [4] can effectively guarantee asymptotically close to optimality, it remains to be studied whether it can be applied to different quality metrics.

3.2 Model-Based and Model-Free Approaches

Motion control is mainly to solve the problem of how to control the target system to accurately track the command trajectory, that is, for a given command trajectory, select a suitable control algorithm and parameters, generate output, and control the target to track the given command trajectory in real-time and accurately. In this section, the main research is the application of model-based and model-free (data-driven) methods of reinforcement learning to the robotic arm in the past five years.

Reinforcement learning is a branch of machine learning that emphasizes how to act based on the environment to maximize the expected benefits. The biggest feature of reinforcement learning is learning in interaction. The environment gives the robot a reward system, so it continues to stimulate the robot to produce better actions. As pointed out in [9] that reinforcement learning offers to robotics a framework and set of tools for the design of sophisticated and hard-to-engineer behaviors. Reinforcement learning can be divided into two types: model-based and model-free learning. In the model-based, the robot can perform a demonstration in the simulation environment of the current environment, and use this simulation to plan and control the robot. In model-free, the robot cannot obtain the simulated environment of the current environment, and the robot's continuous attempts to change its motion and planning.

A model-based motion planning for industrial manipulators with sensors for shape inspection tasks was proposed in [10]. The inspection work using the 6-degree-of-freedom industrial manipulator must first complete the determination of a set of viewpoints of an inspected object, also called view planning, and secondly determine the trajectory of the collision-free robot with the best viewpoint, which is called the path

Table 3. Motion planning algorithms.

Algorithms	Year of publication	Main features	Advantage/disadvantage	Optimization
Asymptotically Near-Optimal RRT for Fast, High-Quality Motion Planning [4]	2016	The lower bound tree-RRT (LBT-RRT) is proposed, which is a single-query sampling-based motion-planning algorithm that is asymptotically near-optimal	Advantages: Compared with RRT, the algorithm can produce high-quality solutions and has a shorter running time	This algorithm allows continuous interpolation between the fast RRT algorithm and the asymptotically optimal RRT* and RRG algorithms
An indoor path planning and motion planning method based on POMDP [6]	2017	A special planner is designed, and then the solution method of planner is studied based on the DESPOT algorithm of POMDP, which improves the adaptability and safety of the robot indoors	Advantages: High stability of mobile robots to avoid dynamic obstacles; Disadvantages: Only experimental studies were conducted indoors	The quality of the output path algorithm is improved based on artificial potential field and A* algorithm
Randomized Physics-Based Motion Planning for Grasping in Cluttered and Uncertain Environments [7]	2018	This article proposes a physics-based motion planning strategy for crawling operations in uncertain environments. Planning trajectories through internal and external cell exploration (KPIECE)	Advantages: It can provide collision-free gripping trajectories in chaotic and uncertain environments	Enhance the function of KPIECE by exploring trees to a safer area

(continued)

Table 3. (*continued*)

Algorithms	Year of publication	Main features	Advantage/disadvantage	Optimization
Risk-DTRRT-Based Optimal Motion Planning Algorithm for Mobile Robots [8]	2019	A risk-based dual-tree rapid exploration random tree algorithm (Risk-DTRRT) is proposed, which is suitable for most service robots to improve the quality of its motion planning	Advantages: This method has better performance in static/dynamic environments	The algorithm inherits the completeness of the RRT algorithm and provides homotopy-optimal trajectories on the basis of heuristic trajectories

planning problem. In this study, the geometric information of the target object was got by the 3D scanner installed on the robotic arm, so the model-based view planning method is more in line with the study. The method views planning problem as a Set Covering Problem (SCP), which uses combinatorial optimization to select its subset from a large set of viewpoints. The overall motion planning process needs to connect the determined viewpoints according to the robot path with the shortest collision-free cut distance, so as to ensure that the robot will not be damaged when running the task. The path planning problem is regarded as the Traveling salesman Problem (TSP). This method first combines SCP and TSP into a sorting optimization problem called Set-Covering-Traveling-Salesman-Problem (SCTSP) and uses a random key genetic algorithm (RKGA) to solve. The running process of this method is shown in the following Fig. 2:

The robot model, sensor parameters and target object model are required inputs for this method. A random sampling process of viewpoints is performed on the Euclidean space around the target object to generate candidate viewpoint positions. Then each candidate viewpoint sampled is input into the IKFast [11] inverse kinematics algorithm to generate the corresponding robot pose, and the flexible collision library (FCL) is used to test whether the robot collides with the sur-rounding environment until a valid robot pose is found. Next, assess whether the viewpoint is visible through the 6-degree-of-freedom position and orientation of the viewpoint. At the same time, ROS [12] and MoveIt! [13] are used to calculate the collision-free path between the robot poses of the selected viewpoint. Use the rapid exploration random tree connection (RRT-connect) algorithm [14] in the Open Motion Planning Library (OPML) [15] for path planning, which can provide high-quality robot paths in a short time. Finally, use RKGA to solve the sequencing SCTSP. The implementation of this method is based on the model, which greatly improves the efficiency of the inspection task on the automated production line. Towards the issue of motion planning of a vibro-driven underactuated robot [31], some studies propose novel approaches by considering dynamic frictions [16], energy efficient

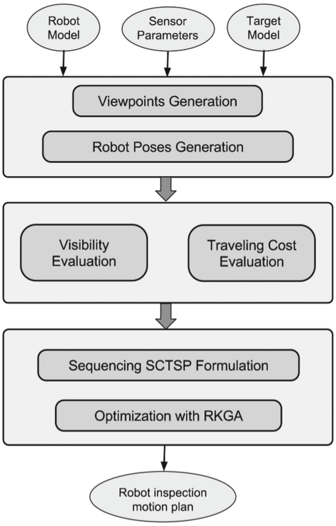

Fig. 2. The brief flowchart of the motion planning method in [10]

design [17], viscoelasticity [18], underactuated motions [19] and optimization-based control [20].

However, the model-based control approach is applied to tasks with large differences in modeling, and the task cannot be completed well or may even cause damage to the machine. But the model-free method can overcome this problem. Regarding the model-free method, Abouaïssa H and Chouraqui S proposed a model-free control method for the robotic arm [21]. The new settings of its related intelligent Proportional, Integral and Derivative (iPID) regulators can handle the control of highly nonlinear and uncertain systems. In this study, a model-free controller was used to control a 6-degree-of-freedom PUMA 560 robot system. Continuously updated local modeling can be obtained through input-output. The control algorithm is based on this local modeling to control the system without any mathematical model of the system. According to the author's simulation experiment, it is not difficult to see that this technology is very effective in controlling the robot arm. This method is robust having good performance, and has high tracking accuracy, and has high industrial application potential. An adaptive neural network tracking control scheme was proposed in [22] for underactuated robot with matched and mismatched disturbances. A trajectory generation method based on Probabilistic Movement Primitives was discussed in [5] to improve the local trajectory optimization. A single trial classification method was studied in [23] based on ERD/ERS and Corticomuscular Coherence. A novel weakly-supervised approach was proposed in [24] for RGB-D-based nuclear waste object detection.

3.3 Handling with Rigid and Soft/Deformable Objects

In terms of robot manipulation, research in the field of manipulation and grasping has been focused from a fixed experimental environment to a daily living environment. As the types of objects increase, its difficulty also gradually increases. Tactile sensation is one of the important ways for the robot interacting with the environment.

A new tactile-array sensor based on flexible piezoresistive rubber was studied in [25], which also implemented in robotic grippers. Put the sensor on the robot's grippers, and after squeezing the execution object, the robot can explore the material characteristics of the object and generate corresponding tactile information to classify rigid and deformable objects. The sensor has the advantages of flexibleness, high resolution, easy installation and easy manufacturing. In this case, in order to further improve the performance of object classification, visual sensors can be used to supplement it [26]. introduces a scheme that can handle polymorphic learning. This scheme can learn manipulation skills from humans and can also learn through other forms of robots. This method allows the robot to manipulate partially soft and rigid objects (such as the flipping skill of nunchaku). If this fusion technology is learned from the definition, then it may be possible to learn from multiple different subjects separately, and to study and test more objects. A robotic arm with a cheap air pressure sensor was proposed in [27] to carry out experimental research on grabbing unplanned objects, using two cooperating schemes based on advanced machine learning (random forest) and parameterized method. The available data come from the actuator position (one per two link finger) and the force sensor value (eight for finger). Through the mutual promotion of the two methods, the overall result is improved in a synergistic manner. Using the robot's haptics provides a system with lower computational complexity and complexity overhead. This scheme will improve classification accuracy and help to estimate the object pose.

Regarding the research of soft (deformable) objects [28], a feedback method was proposed in [29] which can automatically servo-control the 3D shape soft objects through the robotic arm. This method uses a new online algorithm to estimate the unknown deformation parameters, and then manipulates the unknown elastic objects through the model-free controller. A model-based approach that uses robotic multi-finger hands to manipulate deformable objects was proposed in [30]. This method uses the finite element method (FEM) to model the object, then uses the unified representation method based on the Lagrange multiplier to model the contact force, and finally calculates the appropriate contact force on the fingertip by inverse simulation technology to achieve deformation control.

4 Discussion

After literature research, it is found that the most popular and most used basic algorithm is still based on sampling. In the future, we can also conduct further research through these new algorithms in real environment. It is also found that there are many more effective algorithms such as optimization-based [4], Probabilistic Movement Primitives-based [5] and physics-based [7] methods are feasible research directions to explore to improve the effectiveness. And they all have good performance in the benchmarks currently provided, but the benchmarks have hardly been updated in recent years. In future work, more research on motion planning algorithm is needed, and its evaluation benchmarks should be updated to see if more accurate and better evaluation benchmarks can be obtained. On the other hand, it is also necessary to combine these latest research results with real-world applications so that they can provide higher quality services for humans.

In recent years of research, the ability to manipulate objects has been a prevailing direction for robot manipulation. With the development of technology, soft objects and rigid objects have many methods to be classified and manipulated. Although the new sensor proposed in [25] has good results in terms of recognition rate, in the future, different manufacturing methods should be used to increase the resolution to ensure good repeatability. And the sensor model should also be put into the real tested in robot applications. The polymorphic learning scheme introduced in [26] enables robots to master advanced human skills that have not yet been mastered by robots now, especially those involving highly dynamic manipulation, inconsistent materials, and rich interactions. In future work, the scheme can be introduced into definition learning to allow learning from multiple different robots and testing different objects. The use of vision and touch to extract the attributes of objects is the natural sensory ability of humans and animals, but for robots, these two ways of perceiving nature still have many limitations. [27] classifies objects and extracts features through tactile sensors. This principle may be applied to the inspection, sorting and packaging of some objects on the production line. Although other robots can perform more accurate parameter identification on a single object, this method has the ability to identify the characteristics of multiple objects, and it provides more promising results.

In recent years, more attentions have been turned to variable objects, so that robots can classify and operate more objects. [28] proposed a new adaptive method to automatically manipulate unknown elastic objects. Compared with most controllers, this method does not need to identify the deformation model of the object. However, this method is only suitable for slow-moving robots and cannot be used to control rapidly changing objects. In the future, a simpler method needs to be developed to control the shape without using manual marking. The scheme mentioned in [29] can use a robot's multi-finger hands to manipulate variable objects, and this scheme provides a good solution for robots to use multi-finger hands to manipulate soft objects. In the future, visual feedback can be used to improve its inverse simulation and deformation control.

5 Conclusion

Motion planning algorithm is essential for robot to achieve a safe, collision-free trajectory. This article has conducted literature research on the motion planning problem of robotic arm, exploring from model-based to model-free approach to manipulation of rigid and non-rigid (deformable) objects. We discussed the latest advances in these fields in recent years, and briefly described the future trends. In the aspect of motion planning, we should continue to develop new algorithms, and at the same time study the evaluation benchmarking in order to better evaluate different algorithms. In terms of model-based and model-free approaches, we should continue to find new and better Model-free methods, and apply existing methods to the practical environment. In the manipulation of rigid and non-rigid (deformable) objects by robots, research on the operation of variable objects is required, so that the robot can handle different objects effectively and perform more complex tasks.

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