Proceedings of CONF-MSS 2026 Symposium: Mechanical Control and Automation
DOI: 10.54254/2755-2721/2026.BJ31684

Obstacle Avoidance Control for Robotic Manipulators in Unstructured Environments

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Abstract. Obstacle avoidance is one of the core competencies of robotic manipulators that will be performing operations in an unstructured environment, with dynamic situations, incomplete perception, and variable distributions of obstacles. Unlike other organized industrial contexts, this type of environment requires robots to perceive, interpret, and act on uncertainty in real time and, at the same time, maintain the safety and efficiency of their tasks. In this paper, a detailed research of obstacle avoidance systems of control that can be applied in the robot manipulator is carried out in unstructured environments. The existing methods can generally be categorized into reactive sensor methods and model-based pre-planning techniques. Reactive approaches, such as artificial potential fields and locally sensor-based control, have low-Latency reaction but lack awareness of the global position and local minima. Model-based methods, in contrast, build a representation of the environment, such as a point cloud or a voxel map, and solve obstacle avoidance by either an optimization or a sampling-based planning problem, thus naturally solving complicated constraints and global goals. Recent studies in learning-based planning, which include reinforcement learning, imitation learning, and the vision-language-action (VLA) models, are reviewed. Especially regarding their ability to generalize test environments into real cases. Lastly, the strengths and weaknesses of different obstacle-avoidance paradigms are then discussed, and the future research directions towards strong, scalable, and intelligent manipulation in unstructured environments are outlined.

Keywords: Obstacle avoidance, robotics, unstructured environment

1. Introduction

In recent years, the development of robotics has been surging, from stationary robotic arms to standing manlike robots, which have transformed human life completely. However, due to the limitations of their movement and structural space, robotic arms are mostly employed to function in a factory, working on streamlined production in which obstacles are known, collisions are avoided by setting them apart, and the trajectory of arms is manipulated accurately by algorithms [1]. Nonetheless, as robotics is introduced on a broader social scale, people are eager to apply it in a range of industries such as agricultural planting, medical assistance, and disaster rescue. It needs robots to work in an unstructured space, so it has to deal with the problems caused by obstacles, unknown surroundings, and quick responses. Sometimes, how things move around can be hard to

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anticipate because the environment is dynamic. As robots navigate in an open area, the robot's route cannot be planned ahead of time; instead, it must be adjusted simultaneously as the situation changes. Also, the environment is typically unknown or partially observed. Partial observability creates a cosmetic and biased picture of the environment that makes it hard for planning algorithms that need an exact geometric picture. Also, unstructured environments tend to have irregularities and complex geometries that further perplex the model.

Traditional avoidance approaches, such as APF, have a local minimum issue, and they cannot properly handle unconstructed space obstacles [2]. Recently, robotic manipulation obstacle avoidance studies have moved away from traditional offline planners to online controllers and learning-based methods. Researchers have even explored using bio-mimetics by looking at how animals migrate in nature [3]. This paper sets out to construct a standard for continuous research, which is important for fixing major issues and developing robotic arm technology. Furthermore, an instant obstacle avoidance plan within an unconstructed area is the main topic of this article; we have split the avoidance method into two types: global pre-planning methods and local path planning methods. Global motion analysis looks at the environment as a whole using models, then using algorithms such as Dijkstra and A* to find the best path [4,5], which are covered in Section 2. Additionally, machine learning based methods are the main focus in Section 3.

2. Sensor-based obstacles avoidance and reactive control

Sensor-based reactive obstacle avoidance is a process whereby robots react and respond directly to the sensor feedback and commands, and thus manage to avoid the obstacle successfully. Without a preplanned route of the surroundings, the sensor-based arm detects localized regions, and hence processes these and modifies action in response to the data obtained, forming a perception and movement loop [6]. This mechanism allows low-latency response to environmental variations and has been extensively applied in time-changing situations.

However, there are two vital limitations. The automatic reactive approaches are sensor-based, and therefore, the global knowledge of space is not provided, which may cause possible oscillation and sub-optimal paths. A disadvantage of a robot is that, unlike the human body, robotic arms are highly stiff. Moreover, the occlusion threshold of a sensor creates partial observability into the perception process that leads to a lack of obstacle information or unreliable obstacle information. These constraints led to more detailed research on the integration of global planning and multi- sensors into real-time control.

2.1. Feedback based on traditional model

The artificial potential field (APF) method is a classic reactive obstacle avoidance approach that was proposed by Khatib in 1986, in which he modeled robot motion forces as particles moving under the influence of virtual potential forces in space. In this scheme, attractive potentials guide the robot toward the target, while repulsive potentials are generated around obstacles to prevent collisions, and the resulting control action and direction are determined directly from the resulting force of the combined potential field [7]. Due to its low computational complexity and direct transcription from input to output, APF was considered particularly suitable for solving the real-time avoidance dilemma.

However, people later found it to be less feasible due to a detrimental local minimum, where the robot would remain stationary. Koren et al. raised four principal problems with the potential field method, which could be attributed to local minima and oscillation [8]. At a local minimum, the

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resultant force vector is zero, which means that attractive and repelling contributions are in balance. As a result, robots are likely to get stuck in complex aisles, such as U-shaped corridors. Another important disadvantage becomes noticeable when a robot moves through barriers or other tight gaps; any resulting unstable movement can trigger unwanted vibratory behavior. It can lead to undesired situations.

Despite these important limitations, the artificial potential field (APF) approach has still been an extremely popular active method in obstacle-avoidance problems, due to its computational simplicity and fast response during the past decades. Various improvements have been sought for APF by the researchers. Common methods include damping or remodeling the repulsive forces near the target, the use of the least safe distance, relative distance, affixation points, optimization of the potential function, and the use of techniques such as the Gaussian transformation. More so, maneuvers like force-field rotation are utilized to steer the robot through local minima, hence producing a reliable and real-time path plan in tricky settings [9-11]. All these methods provided a new look to APF, but as Artificial Intelligence has developed enormously in the last few years, a vast majority of researchers have shifted their focus to combining AI with obstacle avoidance.

2.2. Multiple-sensor-based avoidance

APF and other sensor-based methods all rely heavily on the sensor's functionality. To address the limitations of single-sensor performance in unstructured environments, multi-sensor-based obstacle avoidance has emerged as a widely adopted approach. The nature of single-sensor strategies indicates their vulnerability to noisy and occluded images and limited fields of view, which cause unstable or unsafe avoidance behavior [12]. Therefore, the key to successful obstacle avoidance is the integration of multiple sensors. The Canonical Multimodal sensor setup is based on Light Detection and Ranging (LiDAR) and Inertial Measurement Units (IMUs). IMU supplies high-frequency motion prediction, and external sensors obtain and visualize pictures of the environment, combined to provide precise and sturdy state estimation of robot navigation and the utmost route planning. The Visual-Inertial LiDAR-based legged navigation system (VILENS) by Wisth et al., made a significant step towards decreasing the localization errors and increasing system robustness by integrating visual, IMU, and LiDAR data, using factor-graph optimization [13]. Tactile sensors, in combination with LiDAR, are also an example of a successful multimodal approach that reduces close-collision hits, which cannot effectively be detected by LiDAR, further enhancing the situational awareness of the robot of the surrounding unknown world. In short, this auxiliary sensing model supplements perception and stabilizes reactive obstacle avoidance controllers.

3. Optimisation based obstacle avoidance methods

In contrast to reactive strategies at obstacle-avoidance, in which the main tool is instantaneous sensor feedback, model-based intelligent pre-planning methods directly build a model of the environment, thus providing a more detailed image of the entire configuration space. Such a method allows predicting the state of the prospective robots and evaluating the potential conditions of the robot and the possible collisions. The premise of such approach is the modeling of the environment, which consequently is the predictor of the complexity, solvability, and speed of the ensuing planning algorithm.

The voxels (volume pixels) are distributed on a three-dimensional grid so that their positions (spatial) as well as other attributes associated with them are encoded. One such case is the use of an octree in obstacle avoidance [14,15]. What makes the benefits of voxelization stand out is its flexibility, which can readily adjust to the dynamic environment as the voxels can divide the challenging spatial domain into a solvable hierarchy, which further allows one to react to the situation in real-time. Yet, there is a trade-off in the unit cube size selection, which a small voxel would face significant computation burden and storage cost, and on the other hand, a large voxel faces significant loss of accuracy due to loss of salient surrounding information [16].

3.1. Trajectory optimization and sampling-based planning method

Trajectory optimization formulates the obstacle avoidance problem as a continuous optimization problem with a collision-free path being the solution to find a minimum scalar cost functional, subject to system dynamics and environmental constraints. To elaborate, the cost function controls the collision avoidance, smoothness of the trajectory, performance time, and energy consumption, which determine the path obtained. Canonical Hamiltonian Optimization for Motion planning (CHOMP) is a formulation of obstacle avoidance as a functional gradient descent in trajectory space, which balances smoothness metrics with local collision costs to generate a locally optimal trajectory without explicit obstacle discretization [17]. Trajectory approaches provide smooth, high-quality, dynamically feasible solutions and are also very effective when a starting feasible trajectory is provided. However, their effectiveness relies on the faithfulness of environmental models and the quality of the initialization.

Unlike the methods of trajectory planning, which refine an initial path found by methods, optimal sampling-based planners find collision-free trajectories by probing the configuration space or state space with randomly selected samples. These techniques overcome the local optimality of gradient-based optimization that guarantees probabilistic completeness. Numerical succession to the global optimum is theorized with the growing number of samples. The outstanding representatives of such a paradigm are the Probabilistic Roadmap Method (PRM) [18] and Rapidly-Exploring Random Trees (RRT) [19]. RPM produces feasible paths via a learning period and a query period. In the learning phase, a random configuration in space is sampled to construct the final roadmap. Then, the query phase: Connect the goal configurations to the roadmap to complete the path search. In contrast, the mechanism of RRT is by growing a tree shape from the starting point, moving all the way to the destination point. During the planning process, the algorithm will randomly sample configuration points within the configuration space and try to connect these configuration points to the nearest node in the tree if it is in the free space. RRT is more suitable for single-query sampling situations since the learning stage is usually disregarded. Optimal sampling-based planners are less dependent on initial conditions and better suited for highly non-convex environments compared to trajectory optimization methods.

3.2. Machine-learning-based intelligent path planning method

Although optimization-based and sampling-based planners have been demonstrated to guarantee reliable theoretical results, their use is inherently limited by the necessity of environmental modeling as well as cost functions, which inspires the development of learning-based, intelligent planning techniques.

Machine learning (ML) refers to machines managing how to grip, avoid obstacles, interact, and perform tasks that typically require human intelligence by learning from experimental data and constantly improving themselves during this process. With the inclusion of AI, robots are capable of perceiving a sense of their environment, responding, making wise decisions, and carrying out complex tasks [20]. New techniques in reinforcement learning, imitation learning, and VLA models

DOI: 10.54254/2755-2721/2026.BJ31684

have built on learning-based planning and enabled robotic manipulators to adapt to a wide variety of unstructured environments.

The part of machine learning known as reinforcement learning (RL) represents the obstacle avoidance behavior as a series of choices in which the robot learns a policy by maximizing the total accumulated rewards of the interaction with the environment. Specifically, unsafe actions such as collisions or near colliding situation are strongly punished, and the reward, which is goal-reaching motions and energy optimum path, takes the form of the R (s, a) [21]. With repeated interaction, this policy can capture the subtle relationship between space, the learning machine, and control action, which in turn helps to solve complicated and dynamic obstacle topographies. Critical problems, however, occur in RL. The training process requires gigantic volumes of interaction data, most of which are collected and consumed during simulated situations due to safety and data-efficiency considerations, leading to a generalization concern.

IL is a method of learning control policies that exploits expert demonstrations to teach the control policy. Under this paradigm, the expert behaviors, produced either by human operators or classical motion planners, can give collision-free trajectories that act as guidance to the policy learning. The demonstrations have taught the robot to avoid actions and imitate the same behavior in similar environmental conditions based on the information the robot has acquired during the demonstrations. IL is more efficient in data, and the training process is safer because the learning process does not demand the robot to investigate potentially dangerous states [22]. However, IL becomes compromised when it is applied in unstructured environments. Distribution shift is one of the big issues a trained policy must encounter in case states are not adequately presented in the training demonstrations; smaller errors can develop exponentially and place the robot in danger.

VLA models indicate a new development in the learning-based planning approach where visual perception, natural language understanding, and action generation are built into one model. Contrary to the RL and IL methods, which tend to have operations majorly at the level of motion or control, the VLA-based methods introduce semantic reasoning into the obstacle avoidance process, allowing robotic manipulators to read high-level task descriptions. VLA models do not normally compute collision-free trajectories in obstacle avoidance problems. They, instead, offer directions on a high level that guide other modules of planning and control. Being aware of semantic information, robots are also able to give precedence to obstacle-avoidance actions according to the context rather than perceiving all obstacles equally. Consequently, it allows robots to act in a more natural and social way in human society. Additionally, VLA facilitates generalization to tasks due to its extensive training datasets. The effectiveness of using VLA models has been proven. Li et al. developed a RoboNurse-VLA to assist physicians during surgery, enabling them to achieve proper grasping and complete handovers in dynamic environments under the guidance of surgeons, with remarkable success in real-life situations [23].

However, the future of VLA in robotics is spoiled by possible constraints. The inaccessibility of large-scale and well-aligned data is one of the fundamental problems of VLA models. The training data must meet all of the visual, language, and action needs. It requires a large, diverse, and comprehensive dataset. Scientists have yet to discover a database that meets all three dimensions. Vision-language datasets that are web-scale have linguistic and visual diversity and no action annotations; robot demonstration datasets do possess action information, but are generally insufficient in language variety. The combination of these could pose a daunting challenge that prevents the practical application of VLA because it is expensive to gather high-quality robotic demonstrations.

Although having excellent functionality, all the learning-based planners are generally very sensitive to training data accuracy and variety, and their performance can struggle when data is distributed differently, or the sensor is noisy. Additionally, the costs of computing are also a major challenge to the implementation of ML robotics.

4. Conclusion

As the use of robotics skyrockets in various industries, the development of an effective avoidance method seems urgent. Inspired by this trend, this paper systematically reviewed obstacle avoidance strategies for robotic arms operating in unstructured environments, where dynamic, uncertain, and geometrically irregular conditions fundamentally challenge traditional planning and control methods. The review categorizes the existing methods into two major groups: sensor-based reactive obstacle avoidance approaches and model-based intelligent preplanning techniques.

Sensor-based methods mainly depend on immediate sensor feedback to produce avoidance actions via quick perception-action loops. Although these methods suffer from local minima, they are highly responsive and robust in a dynamic environment.

In order to overcome the drawback of single-sensor perception for reactive control, multi-sensor fusion appears as a solution. Multi-sensor systems can give a much better and more constant view of the world around them by putting together different kinds of compatible sensors, such as sight, laser detection and ranging (LiDAR), and feeling things with your hands (tactile feedback). Although there are many benefits to using multiple sensors, problems, such as increasing the complexity of the system and increasing the amount of computing required, arise as a tricky obstacle.

Despite its drawbacks, model-based intelligent pre-planning algorithms show the environment with pictures and solve obstacle avoidance as a robot's planning problem. Environment modeling methods such as point clouds, occupancy grids, and voxel-based ones are important for making the planning issue more complicated or easier to solve. Trajectory optimization and Sampling-Based Optimization are derived from these techniques. Trajectory optimization algorithms provide smooth, dynamic motion and incorporate various safety and energy efficiency-related constraints. RRT, optimal sampling-based planners are called optimal planners because they offer theoretical probabilistic guarantees of completeness. And so, they are suitable for high-dimensional planning tasks. However, their need for accurate environment models indicates a high computation cost.

In recent times, learning-based planning methodologies have been established as a solution to problems facing traditional methods. RL and IL can be implemented to teach robotic systems avoidance strategies based on interaction data or expert demonstrations, and the novel VLA provides new avenues for employing high-level semantic reasoning to path-planning. Taken as a whole, these methods display great potential in dealing with dynamic and unforeseeable environments. This makes them favorable in terms of modern robotic systems.

Therefore, a synthesis between these two modalities, as they confer the respective advantages of each, is likely to be the basis of effective obstacle avoidance of robotic manipulators. One of the possible directions can be the incorporation of multi-sensor fusion with sophisticated AI algorithms. From an engineering perspective, the practicality of this integration remains questionable. Overall, the problem of obstacle avoidance of robotic manipulators in unstructured scenarios continues to be an open multidisciplinary research problem.

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