Published by :
https://www.ijert.org/
An International Peer-Reviewed Journal

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 14 Issue 12 , December - 2025

Analysis of Trajectory Planning in Robotics: Application in Manufacturing and Smart Technology

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Abstract - Trajectory planning is the act of figuring out a path or series of motions that a robot needs to follow to do a certain job. Trajectory planning is very important in the quickly changing world of robotics since it helps make things more efficient and accurate. This research gives a detailed look at how trajectory planning is used in two important areas: smart agriculture and manufacturing/industries. The first portion of the report goes into detail about the many kinds of trajectory planning methods that are available today. Different methods, such moving through a series of spots, are talked about. The article then goes into detail on trajectory planning in manufacturing, looking at how important it is in different processes and talking about both its pros and cons. The second section is about smart farming and how to use a trajectory planning framework in agricultural robots. The research compares these two different but related fields to show how trajectory planning may be used in many ways in robotics and how it could lead to major technical advances. The report ends with a summary of the most important discoveries and existing practices. It stresses the necessity for more research in this ever-changing field before the future of trajectory planning in robots.

Keywords
Planning a Trajectory
• Robotics
•Automating Manufacturing
• Intelligent Farming
• Planning Motion
• Algorithms for Optimization

I. INTRODUCTION

Trajectory planning is an important part of robotics that involves figuring out the order of postures or configurations that a robot needs to take on, or the path it has to follow, to reach a certain goal. This could be as easy as getting from point A to point B in the best way possible, or as complicated as doing a series of complicated moves in a changing and unexpected environment.

When we think about all the different things robots can do now, it becomes evident how important trajectory planning is. All of these robots need good trajectory planning to work well and safely. For example, industrial robots that do precise and repetitive tasks in factories, autonomous vehicles that drive through complicated city streets, and service robots that interact with people in everyday situations. Trajectory planning is highly important for a hotel-based food delivery robot like "Hotel1A" since it helps the robot move throughout the hotel in a safe and efficient way. The robot needs to be able to find its way from the kitchen to the guest's room while avoiding things like furniture and humans and following the hotel's rules and layout. Not only does the robot need to think about where it will travel, but it also needs to think about when it will get there. To make a robot move in an effective way, you need advanced algorithms that can handle a lot of data and do complicated math in real time. Also, the robot will have to follow the best path every time it has to, not just once. The robot needs to keep changing its path as it passes through the environment based on new information. This could be because the environment has changed (like when you move a piece of furniture) or because the task requirements have changed (like when you change your order at the last minute). This part of trajectory planning, called replanning, is very important for the robot to be able to handle changing and unexpected scenarios. Trajectory planning also has a big effect on how much energy the robot uses. Trajectory planning can help the robot use less energy and work longer by making its movements more efficient. This is especially crucial for battery-powered robots like "Hotel1A," which need to find a balance between performance and power use.

II. RELATED WORK

Trajectory planning has become an important area of research and development in the quickly changing field of robotics. It is very important for robots to be able to move around and do their jobs accurately and quickly. Trajectory planning is very important because it can be used in many different ways. For example, industrial robots use it to do precise and repetitive tasks, service robots use it to interact with people in everyday situations, and self-driving cars use it to find their way around busy cities.

Guodong Liu et al. [1] present a novel approach for dynamic trajectory planning in collaborative robots. At

International Journal of Engineering Research & Technology (IJERT)
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first, a new and simple method using an RGBD camera Kinect is used to find the distances between the person and the robot. After that, the proposed method (RRT-RV) is used to create the trajectory. This method improves the traditional RRT method by adding a constraint factor and combining the RV method. This method takes into account both moving and stationary obstacles. A simulation experiment is also used to put the new method into action and make adjustments to the parameters. Furthermore, a subsequent physical experiment utilizing the RGBD camera Kinect and the UR5 robot is conducted to confirm the feasibility and efficacy of the developed real-time collision avoidance algorithm.

Wei Li et al. [2] show trajectory control once more by showing how important it is to improve solar energy conversion and capture as much solar energy as possible. Nanotechnology is being used in this case to create a hybrid photosystem that combines biological photosynthetic chloroplasts and dual-emissive carbon dots (CDs) to improve photosynthesis by using light more effectively. The CDs made for this purpose absorb a lot of ultraviolet (UV) light and give off bright blue and red light in water, which is exactly what chloroplasts need. In vitro, when these CDs are added to the surface of extracted chloroplasts, the resulting hybrid photosystem makes 2.8 times more adenosine triphosphate (ATP) than the chloroplasts alone. Additionally, the improvement of photosynthesis in living plants caused by CDs has been verified, with a maximum rise of 25% in electron transport rates seen in leaves without CDs. This shows that nanobionics engineering can improve plant performance in vivo. This is the first time that the unique dual-emission property of nanoparticles, especially the red emission, has been used to improve the photosynthetic properties of both extracted chloroplasts and whole leaves by increasing their ability to absorb light. This study presents a viable approach for the building of biological photosynthetic systems utilizing dual-emissive carbon dots to enhance solar energy conversion both in vivo and in vitro, thereby contributing to progress in the domain of nanobionics.

Werther Serralheiro et al. [3] wrote this work, which presents a method for designing a trajectory that maximizes time and energy for a wheeled mobile robot that is not holonomic. The method uses a nonlinear variable change to turn the nonlinear optimization issue into a discrete second-order cone programming problem that can be solved with convex optimization methods. The multi-objective function has two parts: total energy and traversal time. The penalty coefficient is a number that gives more weight to one part than the other. This penalty coefficient makes it possible to find a balance between optimizing total energy and traversal time. The connection between these two goals makes a Pareto Front in the criterion space, which is based on the penalty coefficient. The paper's main idea is to treat the Pareto curve as an exponential function and come up with a method to figure out its parameters. This exponential function can be used to find the Knee Point, which is the best solution that balances time and energy. This methodical method can be thought of as a self-tuning algorithm that figures out the penalty coefficient needed to make the best voltage signals. The proposed method is shown to work by the numerical results.

Shuang Liu and Dong Sun's [4] paper presents a new optimal motion planning technique designed to minimize the energy consumption of a wheeled mobile robot across diverse applications. First, a model is created that may be utilized to figure out how much energy is needed to change kinetic energy and get past traction resistance. This model is the basis for arranging the robot's movements in a way that uses the least amount of energy. The A* algorithm is used to plan the robot's path, and a new energy-related criterion is added to the cost function to make the route more energy-efficient. To make sure that the established path is smooth, the best time and speed for arriving at the stated waypoints are picked to use the least amount of energy. Simulations and testing show that the proposed motion planning method is energy-efficient.

R. wrote in their paper Katoh et al. [5] examine a real-time path planning approach for a manipulator affixed to a free-flying robot in space. The objective is to minimize the energy expended by mechanical viscous friction forces and the resistances of motor armatures during the manipulator's operation. To do this, they present a novel notion known as the “manipulation ellipse under a constant consumed energy.” The efficacy of this proposed strategy is quantitatively validated using computer simulation.

In their research, T. Suzuki et al. [6] assert that most conventional trajectory planners depend on the trapezoidal pattern of end-effector velocity along the intended path within a task space, which can be executed in real time. But this strategy often makes things move slowly because it's hard to think about limits on the size of joint torques or joint velocities. The authors provide an innovative trajectory planner for three degrees of freedom manipulators, grounded in the manipulators' kinetic energy. The manipulators get their electric power mostly from the difference in kinetic energy. Because of this, the suggested method can take into account the limits on the amount of electric power supplied and the speeds of the joints, making it possible to achieve "high-speed motion" within these limits. Also, the suggested solution doesn't need a lot of math and may be used right away.

Z. Vafa et al. [7] examine the prospective functions of robotic manipulators on future spacecraft, including the execution of satellite servicing operations. The dynamic interaction between the manipulator and the spacecraft poses issues in these applications. To solve this problem, a new idea called the Virtual Manipulator (VM) has been created to help simulate manipulators that work in space.

Z. Vafa's study shows that the VM is important for planning and regulating the movements of manipulators on spacecraft. This helps lessen the negative impacts of dynamic interactions between the manipulator and the vehicle. The VM provides a novel theoretical framework for the future design and advancement of space manipulator systems.

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In their study, L. Garcia et al. [8] put suggested a new optimality criterion for planning the movement of wheeled mobile robots. This criterion uses a cost index to compare how close both forward and inverse kinematic models are to singularity. The method stops slip motions, infinite estimating errors, and control operations that can't be done by avoiding singularities. It also keeps the distance from the singularity, which helps reduce the amplification of wheel velocity errors and high wheel velocity values. The suggested cost index can be used directly to improve path-planning and motion-planning methods (such tree graphs and roadmaps) so that the best collision-free path or trajectory can be chosen from many possible alternatives. The authors illustrate the applications of their methodology with an industrial forklift, equivalent to a tricycle-like mobile robot, within a simulated environment. They confirm various outcomes for the suggested optimality criterion and conduct a comprehensive comparison with findings derived from other conventional optimality criteria, such as shortest-path, time-optimal, and minimum-energy.

This literature [9] presents a novel approach to robot route planning that utilizes the equations of viscous fluid, incorporating external influences. This method is different from most potential field methods because it can work in both 2D binary environments with obstacles and free space, as well as weighted regions and uneven natural terrains where the robot's performance is affected by the slope and ground characteristics. The method shows how the viscosity coefficient may be used to control navigation corridors and how external forces on fluid particles can mimic the effects of gravity and friction between the vehicle and the ground. The planner independently generates various routes with comparable costs, so augmenting the resilience of the solutions relative to those obtained from optimal path searches by facilitating adaptability in response to unexpected local disruptions. The research compares the fragrance diffusion approach for a binary universe to a genetic algorithm for a genuine natural terrain.

Zhengzhong Chu and his co-authors [10] look into the problem of path planning for an underactuated autonomous underwater vehicle (AUV) when ocean currents are affecting it. They suggest a deep reinforcement learning (DRL) path planning method based on the double deep Q Network (DDQN) to make it easier for the AUV to plan its course in places it doesn't know. This method is based on an improved convolutional neural network with two input layers that can handle surroundings with a lot of dimensions. The researchers consider the maneuverability of the underactuated AUV in the presence of current disturbances, especially in unfamiliar surroundings. They create a dynamic and composite reward function to help the AUV get to its goal without hitting anything. Simulation research and comparison investigations show that the proposed strategy works well in unfamiliar contexts.

This research [11] presents an ideal trajectory planning method for industrial robots, utilizing a cubic polynomial curve to connect adjacent path points, hence producing a smoother joint trajectory curve. The Yaskawa six-degree-of-freedom industrial robot is the focus of this investigation. Using MATLAB's evolutionary algorithm toolbox, we set up the fitness function and the constraint condition function. We also found the shortest time interval between path points. At the same time, the operation time of the six joints is synchronized between two path locations that are next to each other. We used MATLAB to simulate the optimization results and find the change curves for each joint's kinematic parameters. The results of the simulation show that the trajectory curves of each axis are smooth and continuous, and the kinematic parameters stay within the limits. This shortens the time it takes to move along a trajectory, makes work more efficient, and sets up a way to direct the robot.

In the article "A Review of Spatial Robotic Arm Trajectory Planning" [12], Ye

Dai and others give a thorough analysis of how to plan the trajectory of a spatial robotic arm. They talk about how spatial robotic arms are becoming more and more important in space activities since they can do in-orbit service duties just as well as people can. The authors stress that trajectory planning is the basis for how a robotic arm moves and that the quality of the planning has a big effect on how well the operation goes. They also point out that research on spatial robotic arm trajectory planning hasn't yet created a general framework for categorization, which means that

The present state of space obstacle avoidance trajectory planning and motion trajectory planning. It talks about the core ideas behind and real-world uses of the spatial robotic arm trajectory planning approach. The authors also look ahead to future tendencies in development.

III. METHODOLOGY

A description of many ways to plan a trajectory Depending on the intended result and the challenge at hand, trajectory planning can seem different. We go into great detail on the many ways to plan and create robot trajectories in this section.

Planning based on a grid

Grid-Based Planning is a way to split the surroundings into a grid. Every cell in the grid shows a possible state for the robot. The robot can move to grid points next to it as long as the line between them is totally inside the free configuration area. Collision detection [13] is used to test this. The technique uses grid representation, graph representation, and path planning. The environment is split up into a grid, and each cell shows a possible state for the robot. If we call the grid a matrix G, each cell G[i][j] might be either an open area or an impediment. You can think of the grid as a network with nodes for each cell and edges that connect nodes that are next to each other. If we call the graph Graph(V, E), where V is the set of vertices and E is the set of edges, then each

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
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vertex v in V corresponds to a cell in the grid. An edge (v1, v2) in E exists if the cells that correspond to v1 and v2 are next to each other and have no obstacles. Finding a path on the graph from the start node to the destination node is all that's left to do for path planning on the grid. You can use network search algorithms like A* to do this. The A* algorithm keeps a priority queue of nodes. The priority of a node is determined by:

f(n) = g(n) + h(n)

In this case, g(n) is the cost of the path from the start node to n, and h(n) is a guess at the cost of the cheapest path from n to the target. If the heuristic h(n) is acceptable, which means it never overestimates the cost of getting to the goal, the A* algorithm will always discover the shortest path. You can also use multi-resolution grids to make things more efficient. This method shows the environment at different resolutions, and the algorithm can flip between them while it searches. This lets the algorithm quickly skim over big free areas in low resolution and only switch to high resolution when it has to.

Moving Through a Series of Points

In many cases, the trajectory is made up of more than two points. For a simple pick-and-place procedure, it could be helpful to add two more points between the start and end points. These spots could be the best places to pick up and put down the object, which would let you move it more slowly than if you were moving it directly. For more involved jobs, it could be desirable to build a sequence of points to enable improved tracking of the accomplished courses. These locations should be more numerous in regions of the path where impediments need to be avoided or where the path curvature is considerable. It's vital to remember that you need to figure out the joint variables from the poses in the operational space.

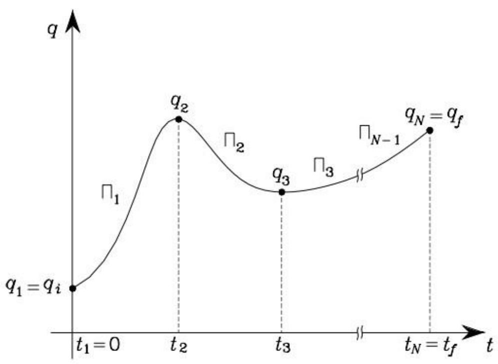

Figure 1: Characterization of a trajectory on a particular path achieved from interpolating polynomials

The issue lies in designing a trajectory that meets N defined path points at certain moments in time, with each joint variable having N limitations. One can try employing a polynomial of order (N-1) for this purpose. However, this strategy has significant drawbacks:

It doesn't allow for the assignment of initial and ultimate velocities.

The oscillatory nature of the polynomial increases with its order, potentially resulting to abnormal trajectories for the manipulator

The precision of calculating polynomial coefficients lowers as the order of the polynomial grows.

The resulting system of constraint equations is computationally intensive to solve.

The coefficients of the polynomial depend on all the assigned points. This means that if one point needs to be changed, all the coefficients must be recalculated.

Planning based on rewards

Reward-based planning, which is widely employed in Reinforcement Learning (RL), is a method in which an agent learns how to make decisions by doing things that will provide them the most reward over time.

There are a few important parts to the math of reward-based planning:

State Space (S): This is the collection of all the different states that the agent can be in. In the context of robotics, a state might show where the robot is, how fast it is moving, and other things like that.

Action Space (A): This is the group of all the things the agent can do. An action for a robot could be an order to move, like "move forward" or "turn left."

Reward Function: This is a function that gives the agent a number for each state-action pair. The agent's goal is to get as much reward as possible throughout time.

Policy (π): This is a function that tells you what to do in each state. In the context of Q-learning, the update rule is:

Q(s,a)⟵Q(s,a)+α[r+γ (max⁡┬(a^') Q(s^',a^')-Q(s,a)]

where:

Q(s,a) is the Q-value of doing action an in state s.

The learning rate is α.

r is the reward you get right away after doing action an in state s.

The discount factor is γ.

Maxa′Q(s′,a′) is the highest Q-value for all conceivable actions a′ in the following state s′.

This equation is used to update the Q-values over and over until they reach the correct values. At that time, the Q-values can be used to find the best policy.

Trajectories in operational space

A basic idea in robotic trajectory planning is the usage of motion primitives. These are pre-computed actions that a robot can do from a certain state. These are very

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important because they show how a robot moves in a straightforward and beautiful way, showing the immediate paths it can follow based on the control inputs it has. There are many different kinds of these, depending on what the robot needs and what it needs to do. They can show basic linear movements, rotations, or more complicated moves. The option can have a big effect on how well the robot works, including how fast it moves, how smoothly it moves, and how well it can avoid obstacles. One of the main benefits is that they automatically meet the robot's kinodynamic limits. Because each primitive is a possible way for the robot to move, every path made up of these primitives is sure to be kinodynamically possible. This means that there is no need to do any more inspections or post-processing on the trajectory that was made. A* and its variants are examples of search-based algorithms that are often employed with them to determine the best path. The search algorithm looks at all the available paths by linking different primitives in different ways. The goal is to identify a series of primitives that gets you from the start state to the end state while keeping the cost function as low as possible, like the total distance traveled or the total time spent traveling. They also make the trajectory planning procedure more reliable. They make it possible to plan resilient trajectories for surroundings that aren't fully known by using a collection of deterministic trajectories. The robot can nevertheless make a reasonable and efficient path by carefully choosing and ordering the primitives, even if it doesn't know the entire structure of the environment or where all the obstacles are. This makes them a great tool for planning the path of a robot.

IV. RESULTS

Real-world application of trajectory planning in robotics.

Guohong Li [11] and his peers set out to design a smooth joint trajectory curve which uses a cubic polynomial and is applied to robots operating in an industrial setup.

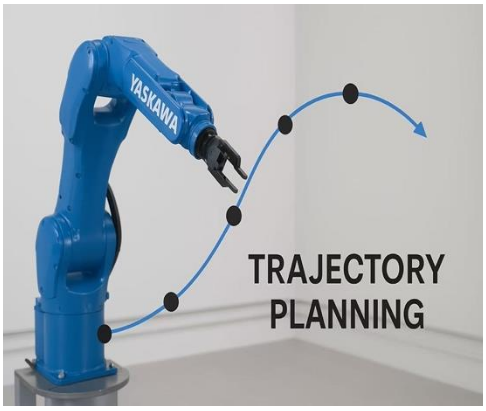

Figure 2: Yaskawa robot subject to the trajectory planning [11]

The robot whose trajectory is being planned, consists of a base, a waist, a big arm, a small arm and a wrist as indicated in figure 2. It has 6 degrees of freedom (DOF).

With the understanding that all six joints must adhere to their kinematic restrictions, meaning that the maximum limits for velocity, acceleration, and jerk for each joint should not be surpassed, the goal is to identify the time series node

that minimizes the total time. The problem the authors had to solve in this case was actually a nonlinear constraint optimization problem. A genetic algorithm implemented through Matlab was deployed to solve the optimization problem

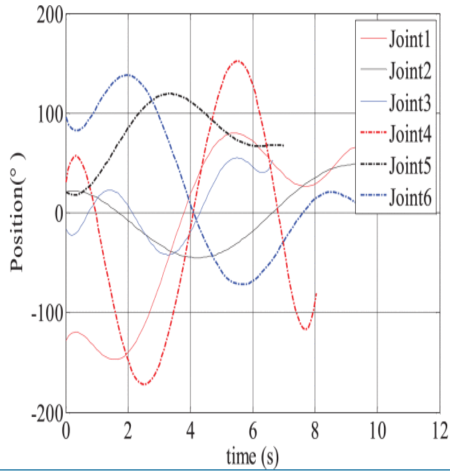

Figure 3: Optimal trajectory from each joint [11]

As seen from figure 3, due to different constraints of different joints, the time for each joint to reach the target position varies. Now the end-effector is required to accurately pass through the path point in the task space, and the rotation time of each joint to reach the path point is the same.

The simulation results show that the running time of each joint is synchronized, the curve of position change and the curve of velocity change are smooth, the curve of acceleration change is continuous, and the kinematic parameters meet the constraint conditions, which effectively reduces the running time of the robot trajectory.

A. Robots in industrial settings

Industrial robotics, a field that encompasses the design, control, and application of robots in industrial settings, has evolved to a point where its offerings are now considered mature technology. Industrial robots are typically designed to function within structured environments where most geometric or physical attributes are known beforehand, thus requiring only a limited degree of autonomy.

The genesis of industrial robots can be traced back to the 1960s, a period marked by the intersection of two key technologies: numerical control machines, which brought precision to manufacturing, and teleoperators, which facilitated the remote handling of radioactive materials.

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
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The initial robot manipulators, compared to their predecessors, were distinguished by several features. They were versatile, capable of using various end-effectors attached to the manipulator’s tip. They were adaptable, equipped with sensors to handle situations not known beforehand. They were accurate in positioning, thanks to the implementation of feedback control techniques. Lastly, they were capable of repeating tasks, due to the programmability of different operations.

Over the years, industrial robots have become increasingly popular and are now seen as vital elements in the implementation of automated manufacturing systems. The proliferation of robotics technology across a broad spectrum of applications in the manufacturing industry can be attributed to several key factors. These include the lowering of manufacturing costs, enhancement of productivity, elevation of product quality standards, and the ability to remove tasks that are detrimental or unpleasant for human operators in a manufacturing system.

Automation, in its conventional sense, refers to a technology that seeks to substitute humans with machines in a manufacturing process. This substitution pertains not just to the performance of physical tasks but also to the intelligent handling of information about the process status. Thus, automation represents a fusion of typical industrial technologies used in the manufacturing process and computer technology that facilitates information management. Automation can be categorized into three levels: rigid automation, programmable automation, and flexible automation

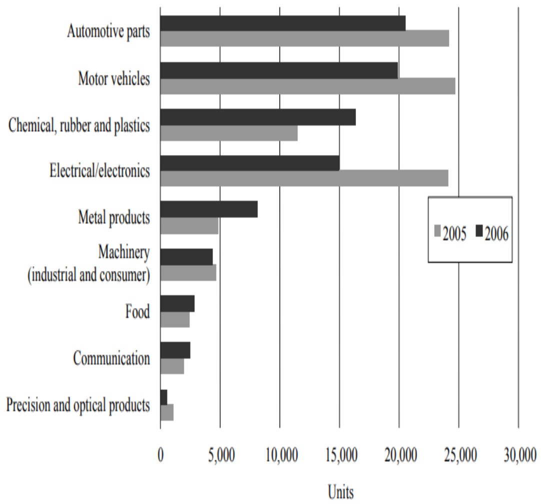

Figure 4: Industry-based robot robots supply

Rigid automation is a concept that applies to a factory setting where the focus is on mass production of identical items. This approach necessitates the use of specific operational sequences carried out by specialized machines to meet the demands of high productivity and quality standards for manufacturing large quantities of parts.

On the other hand, programmable automation is applicable in a factory environment where the production involves low to medium batches of varied products. This type of automation allows for easy changes in the operation sequence performed on the workpieces, thereby enabling a variation in the product range. The machines used in this context are more adaptable and can produce different items that fall within the same group technology. Today, most of the products in the market are produced using programmable automated systems.

Flexible automation is seen as the next step in the evolution of programmable automation. The aim here is to facilitate the production of varying batches of diverse products while minimizing the time spent on reprogramming the operation sequence and the machines used when transitioning from one batch to another. Implementing a flexible manufacturing system (FMS) requires a high degree of integration between computer technology and industrial technology.

A. Capacities of industrial robots

Three core abilities make industrial robots indispensable in a manufacturing process: the handling of materials, manipulation, and measurement. In the context of a manufacturing process, it's necessary for each item to be moved from one part of the factory to another for storage, production, assembly, and packaging. Throughout this transfer, the item's physical properties remain unchanged. The ability of a robot to grasp an item, transport it along predetermined routes, and then let it go positions the robot as an ideal choice for operations involving the handling of materials. Common uses of this capability encompass activities such as palletizing, which involves arranging items on a pallet in a structured manner, loading and unloading warehouses, tending to mills and machine tools, sorting parts, and packaging.

Figure 5: Adept Technology Inc industrial robot, The AdeptOne XL

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In addition to robots, Automated Guided Vehicles (AGVs) are also used in these applications. They are responsible for moving parts and tools across the shop floor from one manufacturing cell to another. Unlike traditional vehicles that follow fixed guide paths (like inductive guide wire, magnetic tape, or optical visible line), modern AGVs are equipped with advanced systems. These systems include onboard microprocessors and sensors (such as laser, odometry, GPS) that enable them to locate themselves within the plant layout and manage their workflow and functions. This allows for their full integration into the Flexible Manufacturing System (FMS). Mobile robots used in advanced applications can be seen as the next step in the evolution of AGV systems, particularly in terms of increased autonomy.

Manufacturing involves the transformation of raw materials into finished products. During this process, a part may either undergo changes in its physical characteristics due to machining, or it may lose its identity as a result of being assembled with other parts. The ability of a robot to manipulate both objects and tools makes it an ideal candidate for use in manufacturing. Some common applications include arc and spot welding, painting and coating, gluing and sealing, laser and water jet cutting, milling and drilling, casting and die spraying, deburring and grinding, screwing, wiring and fastening, assembly of mechanical and electrical groups, and assembly of electronic boards. In addition to handling and manipulating materials, measuring is another crucial aspect of a manufacturing process, which is necessary for assessing the quality of products. Robots, with their ability to navigate 3D space and the availability of data on the status of the manipulator, can be utilized as measuring instruments. They are typically used for inspecting objects, identifying contours, and detecting flaws in manufacturing.

The number of robots used in Europe in 2005 and 2006 for various tasks indicates that material handling required twice as many robots as welding, while only a small number of robots were used for assembly.

Moving on, let's look at some industrial robots and their features and areas of application. Take, for example, the AdeptOne XL robot shown in Figure 5. This robot has a four-joint SCARA structure and uses direct drive motors. It can reach up to 800 mm, with a horizontal repeatability of 0.025 mm and a vertical repeatability of 0.038 mm. The maximum speeds are 1200 mm/s for the prismatic joint, and they vary from 650 to 3300 deg/s for the three revolute joints. It can carry a maximum payload of 12 kg. This robot is typically used in industrial applications such as handling small parts, assembly, and packaging.

Example of applied trajectory planning in autonomous driving

In autonomous vehicle technology, trajectory planning is a critical aspect. However, the prevalent methods, which employ a constant set of weights to identify the optimal trajectory from a group of possibilities, can lead to abrupt alterations in intricate dynamic environments. To address this, Zhilei Chen and his team [14] have introduced a resilient trajectory planning methodology that draws on past data. The method is composed of four key modules: the generation of candidate trajectories, collision detection, stability detection, and speed planning. Initially, candidate trajectories are produced based on the kinematic model of the vehicle. Subsequently, the collision detection module eliminates any trajectories that could potentially lead to accidents. The optimal trajectory is then chosen through a multi-attribute evaluation and examined by the stability

detection module, which measures the lateral deviation of the optimal trajectory from the historical one. Depending on the results, either the current optimal trajectory or the historical one is selected as the output. Finally, the speed planning module uses the output trajectory to generate a smooth path. The efficacy of this approach was validated through simulations and real-world experiments.

How does the method work?

In the work of Zhilei Chen and his team [14], trajectory planning is approached in a systematic manner. It begins with the generation of candidate trajectories based on the vehicle's kinematics model, considering both the initial and terminal states. These trajectories are then scrutinized by an obstacle collision detection algorithm to eliminate any potentially hazardous paths. The remaining trajectories undergo a multi-attribute indicators evaluation to select the optimal trajectory using the latest perception information. This selected trajectory is further examined by a stability detection algorithm, which measures its lateral deviation from the historical trajectory. Depending on this evaluation, either the current optimal trajectory or the historical one is chosen as the final output. The process concludes with a speed planning algorithm that uses the selected output trajectory to create a smooth path, ensuring stable tracking by the control system. The structure of this proposed trajectory planning method is depicted in Figure 6.

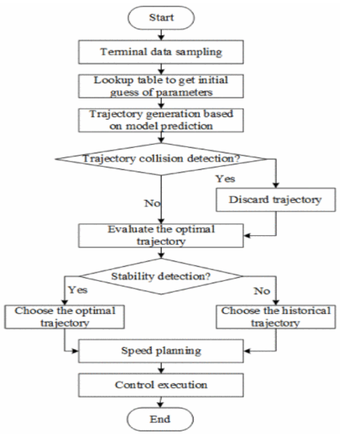

Figure 6: Trajectory planning methodology. Courtesy of [14]

Example of trajectory planning of a drilling system based on ant colony algorithm

In their study, Ping Li et al [15] have proposed an innovative optimization method for trajectory planning in numerical control drilling for panel furniture. This method, based on the elite ant colony algorithm, has been developed through a thorough analysis of the objectives of trajectory planning. The algorithm is designed to prevent falling into local optimums and is compatible with integration into machining center software. Simulation analyses and solutions have demonstrated that this method can decrease the drilling path step by 10.8% in comparison to the empirical law. Further simulation processing using numerical control drilling software has shown that this optimization algorithm can significantly enhance drilling production efficiency.

The authors, in their quest to optimize drilling trajectory path planning, aim to minimize the machining path, reduce idle movement, and enhance NC drilling efficiency. Considering all possible paths for n holes, each path must undergo distance and efficiency comparison, which has a time complexity of 2n. As the number of holes increases, immediate planning results become challenging due to extensive calculations. To address this, the authors introduce the Elite Ant Colony algorithm, which calculates weights based on hole distances, informing the planning of the next hole location. The further a hole location, the less likely it is chosen as the next processing step, and vice versa. This approach significantly reduces planning time, quickly identifies the optimal processing path, improves processing efficiency, reduces mechanical wear, and extends equipment lifespan.

V. DISCUSSION

Trajectory planning in smart agriculture

Trajectory planning in agriculture is an important part of precision farming that uses robots and automation to make sure that farm machinery moves and acts in the best way possible. It means figuring out the best routes for machines to take, based on things like the shape of the field, the type of crop, and the terrain. The goal is to cut down on missed and overlapping regions, use less fuel, and get the most crops. To plan and regulate the paths of autonomous agricultural vehicles, advanced algorithms and technologies like GPS and GIS are employed. This lets them move around fields properly and do jobs like planting, spraying, and harvesting with great accuracy. As the need for environmentally friendly and efficient farming methods develops, trajectory planning in agriculture keeps changing, making room for new and better solutions in the field.

There are also some advanced parts of trajectory planning in agriculture that make it even more useful. For example, machine learning algorithms can look at past data and figure out the best paths depending on how well they did in the past. This makes it possible to plan trajectories that can change in real time based on changing conditions. Also, connecting IoT devices and sensors gives you real-time information about soil conditions, crop health, and weather patterns, which can be used to make trajectory planning even better. Drones are also very important for trajectory planning because they may provide you a bird's-eye perspective of the field and help you plan more accurately. Trajectory planning isn't just for field work; it also includes things that happen after the harvest, such sorting, packaging, and transportation. This makes sure that the whole agricultural supply chain runs well. As technology keeps getting better, trajectory planning in agriculture is likely to get better too, giving farmers even more ways to be more efficient and environmentally friendly.

An illustration of trajectory planning in a Robot Operating System (ROS) design.

Lorenzo Gentilini et al. [16] present an implementation of a Robot Operating System (ROS) service in their research. The goal of this service is to build polynomial paths for an Unmanned Ground Vehicle (UGV). The team ran tests on a tracked robotic platform to see if it could follow a series of waypoints in an open-field navigation environment. A state-feedback controller made this possible. The ground robot uses signals from the Global Navigation Satellite System (GNSS) and motor encoders to figure out how far it has traveled. The team did a detailed study of the experimental experiments and showed the results.

The authors, concentrating on the notion of open-field navigation, confront the difficulty of devising routes through a specified sequence of waypoints, intended to be devoid of collisions. They have come up with a strategy to optimize a trajectory that can find a safe path that goes through the specified waypoints while still following the kinematic and dynamic rules of the chosen Unmanned Ground Vehicle (UGV). This is accomplished by employing the core notion of a hard-constrained trajectory optimization methodology, initially presented in [9].

In reference [9], the authors discuss the controller design and trajectory generation for a quadrotor functioning in three dimensions inside a highly confined environment characteristic of indoor environments. In these kinds of situations, the attitude must be able to change a lot from the hover state, and small angle approximations can't be used for roll and pitch. They have created an algorithm that can create the best paths in real time using a series of 3-D coordinates and yaw angles. This makes sure that the paths are safe and follow rules for speeds, accelerations, and inputs. A nonlinear controller makes sure that these paths are followed exactly. Experimental outcomes validate the method's efficacy for rapid mobility (5-10 body lengths/second) in three-dimensional slalom courses.

Example of trajectory planning in a Robot Operating System (ROS) design

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 14 Issue 12 , December - 2025

In their research, Lorenzo Gentilini et al [16] introduce an implementation of a Robot Operating System (ROS) service. This service is designed to create polynomial trajectories for an Unmanned Ground Vehicle (UGV). The team conducted tests on a tracked robotic platform, with the aim of following a series of waypoints in an open-field navigation setting. This was achieved using a state-feedback controller. The ground robot's odometry estimation relies on readings from the Global Navigation Satellite System (GNSS) and motor encoders. The team carried out a thorough analysis of the experimental tests and presented the results.

The authors, focusing on the concept of open-field navigation, tackle the challenge of formulating trajectories through a pre-determined series of waypoints, which are designed to be collision-free. They have developed a trajectory optimization process that can construct a safe path that passes through the given waypoints, while conforming to the kinematic and dynamic constraints of the selected Unmanned Ground Vehicle (UGV). This is achieved by utilizing the fundamental principle of a hard-constrained trajectory optimization approach, first introduced in [9].

In literature [9], the authors address the design of the controller and the generation of the trajectory for a quadrotor operating in three dimensions in a highly constrained environment typical of indoor settings. In such environments, it is essential to allow for significant deviations of the attitude from the hover state, and small angle approximations cannot be justified for roll and pitch. They have developed an algorithm that enables the real-time generation of optimal trajectories through a sequence of 3-D positions and yaw angles, ensuring safe passage through specified corridors and satisfying constraints on velocities, accelerations, and inputs. A nonlinear controller ensures the faithful tracking of these trajectories. Experimental results demonstrate the application of the method to fast motion (5-10 body lengths/second) in three-dimensional slalom courses.

L. Gentilini et al [16] conducted a real-world test to validate the accuracy of their method, as depicted in Figure 7. They began by driving the vehicle outside the recovery hangar (marked by a red circle) to allow the localization filter to stabilize. Following this, the trajectory_server node computed the path using yellow waypoints. These waypoints are situated on a small road that leads to the start of the rows of fruit trees (indicated by a white circle). At this location, the rover is expected to transition to in-field navigation.

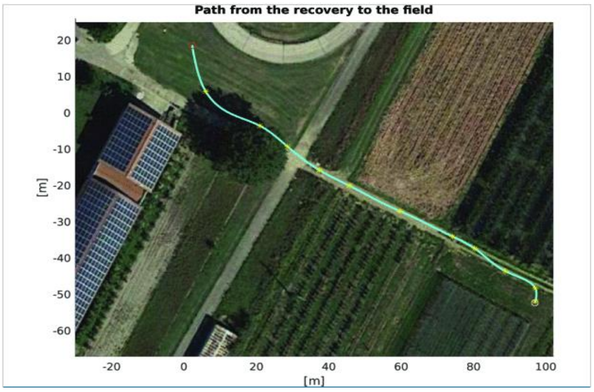

Figure 7: Computed trajectory waypoints from trajectory_server. Courtesy of [16]

The trajectory that resulted from this process had a duration of 201.4 seconds.

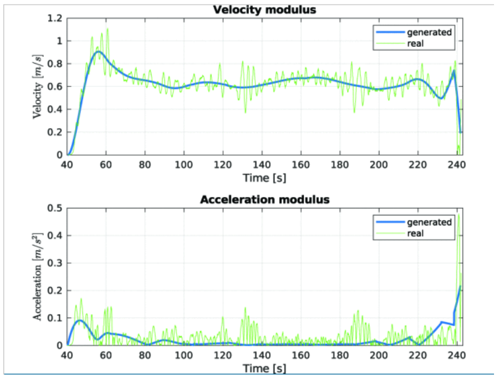

Figure 8: Velocity and acceleration plots from trajectory test. Courtesy of [16]

Figure 8 presents the commanded velocity and acceleration resulting from this process, alongside the actual velocity and acceleration experienced by the vehicle during the trajectory's execution.

1.1. Example of trajectory planning in plant protection robot

In their paper, Ma Jiayi [18] and her team explore the methodology for working trajectory planning for plant protection robots in the arid regions of western China. This is based on the crop arrangement and the unique characteristics of single small area planting prevalent in the region. The study begins with an analysis of the distribution patterns of crops characteristic to the western mountainous region. The robot's motion path is then established in accordance with the crop planting arrangement, and the spray robot's working path is simplified akin to a postman's route. The final step involves the application of the ant colony algorithm to determine the optimal spraying path. This research offers valuable technical insights that supportapplication and advancement of agricultural robots in the hilly regions of western China.

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 14 Issue 12 , December - 2025

2. CONCLUSION

In conclusion, this research has examined the crucial importance of trajectory planning in the manufacturing and agriculture sectors within the swiftly advancing field of robotics. The investigation has highlighted the importance of trajectory planning in diverse industrial processes and its use in agricultural robots, elucidating both the advantages and obstacles involved.

The future of trajectory planning in robots seems bright and full of possibilities. As technology gets better, we should expect trajectory planning to get better and more reliable. The use of artificial intelligence, machine learning, and deep learning algorithms will be a big part of this improvement. These technologies will allow for more accurate forecasts and changes to be made in real time based on things like the weather and the status of the equipment. The Internet of Things (IoT) and big data will also give us a lot of information that we can utilize to improve trajectory planning. You can examine real-time data from sensors and devices to change trajectories right away, which makes things more efficient and cuts down on waste. Also, as self-driving cars become more common, trajectory planning will be very important to make sure these cars can safely and effectively navigate through complicated settings. This includes not only terrestrial vehicles but also drones that fly and vehicles that move underwater, which makes trajectory planning more useful.

Also, trajectory planning can help us save energy and have less of an impact on the environment as we work toward sustainability. We may reduce fuel use and emissions by optimizing pathways, which helps make our practices more environmentally friendly and long-lasting. The future of trajectory planning is full with exciting possibilities and will be at the cutting edge of robotics technology, which will improve efficiency, accuracy, and sustainability. Trajectory planning will definitely be a big part of the future of robots as we keep coming up with new ideas and pushing the limits of what is feasible.

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