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Path Planning for Special Robotic Operations

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Path planning for special robotic operations

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Abstract

The problem of robotic path planning has been the focus of countless investigations since the early works of the 70's and, despite the large number of results available in literature, is still a topic that draws a great interest. In virtually all robotic applications it is required to somehow define a feasible and safe path, and such a problem can be cast and solved in many ways, given the several possible combination of robots - industrial robots, Autonomous Guided Vehicles (AGVs), Unmanned Aerial Vehicles (UAVs), underwater vehicles - and scenarios - a production line, a warehouse, an hazardous mountain - and therefore a large number of approaches and solutions have been, and are being, investigated. The aim of this chapter is to provide an overview of such widespread literature, first by briefly recalling some classic and general-purpose methods used in path planning, then by focusing on some application-specific problems, related to AGVs in industry, medical robotics and robotic welding. This choice is motivated by the prominent relevance of the path planning problem in these three applications. Then, a single application of great industrial interest, such as robotic spray painting, is analyzed. Its specific features are described, and several techniques for task modeling and path planning are considered. A detailed comparison among these techniques is carried out, so as to highlight pros and cons of each one, and to provide a methodology to choose the most suitable one for the specific robotic spray painting application.

1.1 Path planning for general-purpose applications

Autonomous vehicles, mobile robots and, in general, robots, are usually required to move between two - or more - points in space, and solving the path planning problem results in the definition of a feasible and collision-free path to be followed by the robot. Additionally, some metric is usually embedded in the problem solution algorithm to fulfill the improvement of some performance criteria, with the aim of finding an 'optimal' solution. This problem is often intertwined with localization, i.e., the problem of understanding where the vehicle actually is (Akai et al. 2018), and map building (Castellanos and Tardos 2012), i.e., the definition of the map of an unstructured environment during the robot operation. Combining the two problems results in a Simultaneous Localization and Mapping (SLAM) problem (Durrant-Whyte and Bailey 2006; Bailey and Durrant-Whyte 2006).

The extremely vast literature on path planning for mobile robots calls for a comprehensive classification of the several methods proposed over the years: one possibility is to classify the available methods among classical methods - such as roadmap planning or artificial potential field method -, heuristic methods - such as genetic algorithms, neural networks - and meta-heuristic methods, among which Ant Colony Optimization and Particle Swarm Optimization are worth of mentioning. A brief overview is presented here before focusing on more application-specific solutions.

1.1.1   Classical methods

Classical methods refer to the broad range of options that were developed before the introduction of artificial intelligence. The most authoritative references on such topics is the classic book (Latombe 2012), which focuses on roadmap planning, cell decomposition methods, and artificial potential field methods. Roadmap methods refers to a family of algorithms which share the capability of producing a map composed of one-dimensional curves: once the roadmap is built, the best option among the roadmap is chosen. In practical terms, usually the roadmap can be built as a visibility graph (Lulu and Elnagar 2005), i.e., a graph composed of lines that connect the vertices of the geometric representation of obstacles: the result is the shortest collision-free path, but such path is as close as possible to the obstacles (Latombe 2012). If the goal is to move as far as possible from obstacles, Voronoi diagrams are a better method to build a roadmap: such diagrams are defined as the location in space which are equidistant from obstacles. The method based on Voronoi diagrams has found its use not only for mobile robots (Duinkerken et al. 2006), but for UAVs (Davis et al. 2012) and underwater vehicles (Candeloro et al. 2016) as well.

The artificial potential field method was developed in the eighties (Khatib 1986) as a computationally efficient way to produce a collision-free path. The procedure is divided into two steps: the first one aims at defining a suitable number of potential field functions, that comprise both attractive and repulsive fields. Attractive fields are used to drive the robot to its final goal, repulsive fields are used to represents the areas to be avoided, i.e., the obstacles: their sum produces a total potential that must be navigated to seek for an optimal path. Path optimization can be performed either in off-line or on-line fashion. The main strong point of this method lies in its conceptual simplicity, its main drawback is that the total potential field might exhibit local minima in which the robot might be trapped (Rimon and Koditschek 1992). This difficulty can be however overcome by using navigation functions, i.e., by ensuring that the potential field does not have local minima (Connolly et al. 1990) or by adding procedures to escape local minima.

Another classic method that is worth mentioning is the cell decomposition method (Latombe 2012; Lingelbach 2004). In this method a workspace with obstacles is split into regions, called cells. Each cell is numbered, and then translated into a node of a connectivity graph, which collects the information on the reachability of each node. The best sequence of cells that connects the initial and final cell is found by a simple graph search algorithm. The method can be applied to 2D spaces as well as to higher dimension spaces by simply adjusting the structure of the connectivity graph.

Further developments of the 'classic' algorithms have been achieved by introducing random sampling of the workspace, with the aim of boosting the efficiency for large-scale problems.
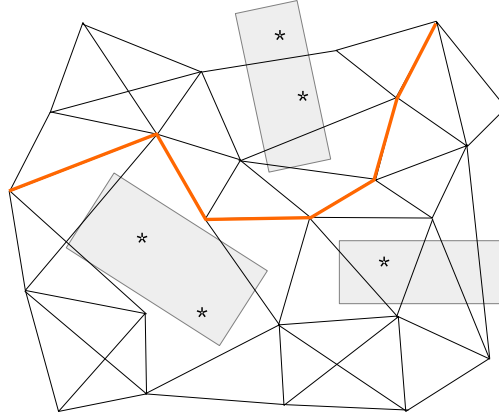
Figure 1.1: An example of probabilistic roadmap path planning.

One example is given by the probabilistic roadmap algorithm, which collects random points within the robot workspace, discards the one that overlap an obstacles, and tries to connect the ones in the free space to produce a feasible path (Kavraki et al. 1996; Geraerts and Overmars 2004). Random sampling is also used in rapidly-expanding random trees (LaValle 1998): in this method a tree structure is build by rooting it to the starting point of the path, then a growing algorithm tests the feasibility of a path built by adding 'branches' after testing the feasibility and measuring the progress towards the designated goal.

1.1.2   Heuristic and meta-heuristic methods

Heuristic methods have been developed since the 90's to circumvent the most common drawbacks sported by classic methods, mainly due to the low efficiency for large-scale problems and local minima trapping (Masehian and Sedighizadeh 2007). Heuristic methods mainly work by using 'shortcuts' to define a feasible solution, often sacrificing a complete exploration of the possible space of solutions, therefore they often trade off global optimality for speed.

Worth of mention is the use of Genetic Algorithms (GA), which have found an extremely wide field of applications, including path planning. Genetic algorithms work by representing a tentative solution to a general optimization problem by representing it as a population, whose evolution is dominated by selection (elimination of non-fit individuals), propagation of the genes to new generation and gene mutation. This method is of very general application, being suitable to the optimization of virtually every problem, with minimal effort on its mathematical representation, as explicit gradients are generally not needed. One of its main drawback is however, the possibility that a true optimal solution is not explored, and as such they are incapable of guaranteeing a global optimum. A basic implementation, as the one proposed, for example, in (Achour and Chaalal 2011), associates a path, represented by a discrete set of point to be visited in sequence, with a chromosome. The initial, necessarily feasible, path, is then altered by creating a new generation, according to the crossover mechanism, followed by the evaluation of the fitness function to be minimized. The best chromosome are selected, to improve the quality of the population. This sequence is continued until reaching a pre-defined stopping criteria. Other early examples of application of GA
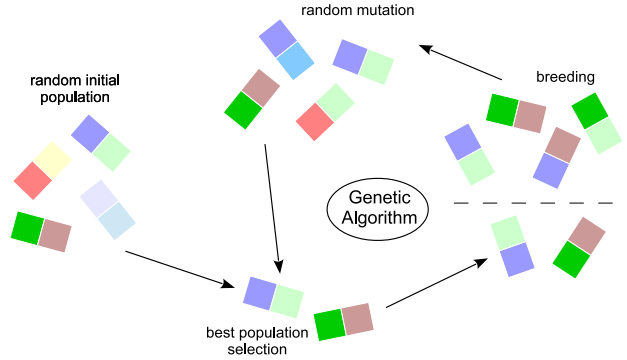
Figure 1.2: Graphical representation of a Genetic Algorithm optimization procedure.

to motion planning include (Shibata and Fukuda 1993; Xiao et al. 1997). A path can be also generated by fuzzy logic, which works by combining several fuzzy rules, that take into account planning-specific goals such as proximity to the final goal, obstacle avoidance, and direction changes (Yen and Pfluger 1991). Alternatively, Particle Swarm Optimization (PSO) has found many applications in path planning: this technique is based on collecting the potential solution of an optimization problem into a swarm of particles. The solution evolves by exploiting the activity of each individual element of the swarm, but as the algorithm progresses, the activity of each particle changes (i.e., it evolves) according to the experience gained by the whole swarm, combining the power of stochastic and evolutionary methods, and exploiting efficiently parallelism (Wang et al. 2018; Zhang et al. 2013).

Another popular biologically-inspired method is the Ant Colony Optimization (ACO) (Englot and Hover 2011; Rao et al. 2018; Wang et al. 2019b), which is a meta-heuristic and probabilistic method inspired by the attitude used by ants to forage food. Ants have the capability of finding the best path to a food source by relying on the traces of pheromones left by other ants. The optimization method somehow reflects this behavior, since the agents, in this case the artificial ants, explore the solution space and leave some long-term memory of the 'trail' run by each ant. The traced are then followed by other 'ants' by exploiting the results of the previous explorations, improving gradually the quality of the solution.

Ant colony optimization has found its first uses specifically in the field of path planning, being this the actual task performed by real ants. In a basic and typical implementations of a path planning method by Ant Colony Optimization (Yu et al. 2020), the representation of the navigable space is obtained by a grid map, which contains both free and forbidden grid elements. The task is to find the path from an initial point to the last one with a minimum number of turns and with the shortest possible path. Each ant follows a path that is built iteratively, and each move to another grid is defined by an heuristic that may vary with the implementation. Each ant then 'marks' the path depositing the so-called 'pheromone trace' - leaving an information on the 'fitness' of the path that is then used by other ants. Iterations are then stopped when reaching a pre-defined goal. Similar procedures can be applied to a graph, rather than a grid map with minimal alterations to the algorithm.

Similar to the Ant Colony is the Bee Colony method (Contreras-Cruz et al. 2015; Bhattacharjee et al. 2011), which combines a global search performed by 'scout bees', and a local search, performed by 'forager bees'. Furthermore, the Cuckoo Search Algorithm (Mohanty
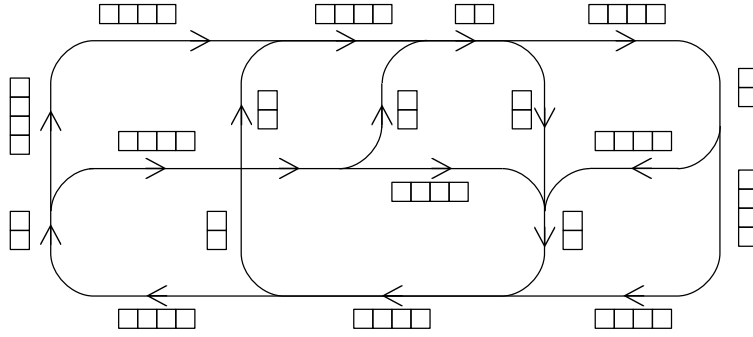
Figure 1.3: A simple route map for a small warehouse.

and Parhi 2016; Wang et al. 2019a; Song et al. 2020) is also experiencing some applications in the path planning of robotic systems.

1.2 Application-specific path planning

1.2.1 Path planning for Automated Guided Vehicles

Since their introduction in the mid fifties, Automated Guided Vehicles (AGVs) are an ever increasingly popular solution for material handling and all sort of transports in industry and logistic centers, as well as in transshipment systems (Fazlollahtabar and Saidi-Mehrabad 2015). Operating a fleet of AGVs requires to solve two issues: the scheduling and the routing problems. While the scheduling problem focuses on the definition of the time frame within which the AGV should move (respecting constraints such as priorities and deadlines), the routing problem focuses on the definition of the route, i.e., the path, that the AGV should move along. Despite being closely related, the two issues are often tackled separately (Qiu et al. 2002). Each of the problem can be technically challenging, especially when the complexity of the scenario is amplified by the numerosity of the fleet of AGVs, that in many cases can comprise several hundreds of vehicles.

Routing problems for AGVs, which are briefly reviewed here, are usually split into two groups, by separating static and dynamic routing problems. A static routing problem solves once for all the target of defining, in advance, the route to go from point *A* to point *B*: if the same procedure is then applied to all possible combinations of two arbitrary points, a list of optimal paths can be defined and stored for later use. Once defined, the route between point *A* and *B* is always used. However, these methods are practical only for static scenarios, since every change in the working environment layout requires to re-compute the optimal paths. The most basic formulation of the routing problem is the well-known Traveling Salesman Problem (TSP), in which the distance to be covered for visiting a sequence of 'cities' and returning to the starting one must be minimized.

In response to the evident limitation posed by static routing problems, dynamic routing problems can developed. Dynamic routing problems can adapt to time-changing conditions, such as layout changes or traffic (Vivaldini et al. 2010).

In most cases, the routing problem focuses on defining shorter paths, as is the case of the early work (Broadbent et al. 1987). In that work, the environment is described by a graph over which the quicker path is found by the classic Dijkstra's algorithm. Moreover, one of

the first examples of conflict-free routing on a bi-directional path network is introduced in (Daniels 1988), which exploits a branch and bound algorithm. A method that is commonly used to reach a conflict-free situation is the use of time windows, as introduced in (Kim and Tanchoco 1991; Kim and Tanchocoj 1993). In the time-window approach each node of the graphs holds the information of free time windows, and an arc connects only the nodes that are not busy by other scheduled jobs.

The literature has evolved over the years striving for computational efficiency and for larger scale scenarios, so the performance sported by the classic Dijkstra's algorithm has been boosted by switching to other search methods, such as the A* algorithm (Wang et al. 2015a), the branch and price algorithm (Savelsbergh and Sol 1998), as well as by using heuristic (Meeran and Share 1997; Bae and Chung 2018; Kulatunga et al. 2006) and meta-heuristic approaches (Tavakkoli-Moghaddam et al. 2008; Farahani et al. 2008; Shirazi et al. 2010). While most methods of path planning for AGVs use graphs to represent the path network, grids can be used as well, as in the case of the works (Yu et al. 2020; Yang and Wushan 2015; Fransen et al. 2020).

The growing popularity of technology based on the Industry 4.0 paradigm is fostering a new stream of research on AGVs, being those a key element in a smart manufacturing environment with high automation level. Smart factories are required to face the challenges of flexibility and reconfigurability (Larsen et al. 2017; Gonzalez et al. 2018), since currently a large part of the commissioning time of a plant is devoted to the generation of collision-free paths. As suggested by the Industry 4.0 paradigm (Indri et al. 2018), the challenges of decentralization, real-time capability, service orientation, and modularity are all to be faced by AGVs, which can be used in fleets of variable size, that can be coordinated either by a centralized system, or by exploiting the on-board sensing and computing capability of AGVs. The work (Nguyen Duc et al. 2020), for example, proposes a neural-network based solution to the route-planning problem that is suitable to real-time applications and compliant with the limited computational capability of most AGVs.

1.2.2 Path planning for medical applications

The history of surgical robots is now more than 30 years old (Camarillo et al. 2004), and currently several medical tasks can be performed, with different shades of autonomy, with the aid of a robot. Common robot-assisted tasks include bone drilling and milling (Louredo et al. 2012), laparoscopy (Nguan et al. 2008) and stereotactic needle placement (Kwoh et al. 1988; Lavallee et al. 1992) just to cite a few notable examples. Despite the quite long history of robotics, in general, and of surgical robotics, there are still several issues that need to be solved: one of them is how to fully exploit the capabilities of a surgical robot to their full extent to improve minimally invasive surgery.

One of the key tasks in surgery is needle insertion (Elgezua et al. 2013), which is a critical operation since it involves the interaction of a long and flexible element, the needle, with soft tissue, that must be performed with precision while providing minimal tissue damaging. Optimizing the needle-tissue interaction requires also to optimize the needle path: this topic is currently under investigation and thinner needles with a bevel tip, called steering needles (Alterovitz et al. 2008) are being developed.

When inserted in a patient's tissue, such needles follow an arc: by rotating the needle
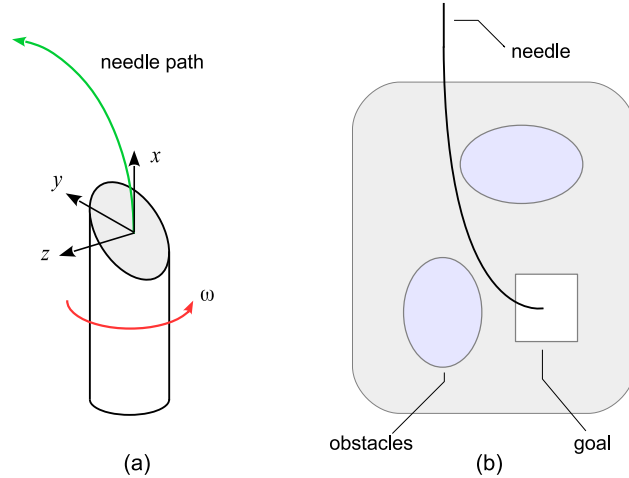
Figure 1.4: Steering needle: principle of operation (a), a typical insertion path (b).
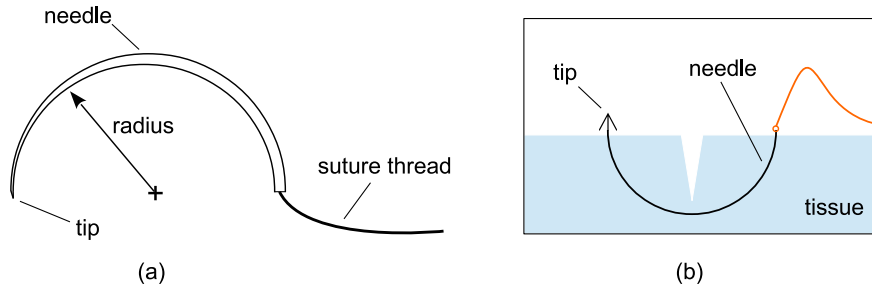

Figure 1.5: A suturing needle (a), a suturing operation (b).

around its axis, a complex path composed by arc can be defined to reach the target area while avoiding obstacles. Since the needle is clearly not visible during the operation, its motion must be carefully planned ahead: in the work (Xu et al. 2008), a Rapidly-exploring Random Trees (RRTs) approach is used to perform this task, adding a backchaining mechanism to define the best needle entry point. RRTs are also used in (Patil and Alterovitz 2010), adding a reachability-guided sampling heuristic to alleviate the sensitivity of the algorithm to the choice of the distance metric. In the work (Alterovitz et al. 2008), the optimal needle path is defined by dynamic programming, using simulations to optimize the performance in a feedback-loop approach. Iterative simulations have been used in (Dehghan and Salcudean 2009), using a fast and gradient-free optimization routine that allows the algorithm to compute the optimal needle orientation and insertion point. Some other steering needle insertion planning methods are based on inverse kinematics of the needle, as in (Duindam et al. 2009), but this method does not ensure solvability for all cases. Alternatively, the classic methods of Roadmaps (Reed et al. 2011) and Artificial Potential Field (DiMaio and Salcudean 2005; Song and Zhiyong 2010) have been successfully applied, but such methods trade off the solution speed for global optimality (Li et al. 2018). More recently, also the Particle Swarm Optimization has been proposed as an effective tool for needle steering planning, as in the case of the work (Cai et al. 2020), showing that a good accuracy can be reached if a proper modeling of the needle-tissue interaction is developed.

Another surgical procedure that can be efficiently performed by robots is suturing, usually performed by specifically shaped needles to join together two tissues by means of a thread (Kapoor et al. 2005). Suturing is a complex operation since its outcome depends on a large number of geometric parameters, such as insertion point, needle orientation, exit point. Moreover, several constraints must be taken into account, and a rather dexterous manipulator must be used. To cope with these difficulties, in the work (Nageotte et al. 2009) the path planning is translated into an optimization problem using the A* solving method (Dechter and Pearl 1985). A general-purpose optimization, such as sequential convex optimization is used for the same task also in (Sen et al. 2016), which has showcased the first case of a fully autonomous stitching procedure, which however is executed at lower speed than the average surgeon. A sensible speedup is predicted in the work (Van Den Berg et al. 2010), in which the motion primitives are not defined a-priori, but they are taught to the robot by a human, showcasing a promising 'teaching by doing' application in surgery.

1.2.3   Path planning for robotic welding

The concurrent developments of welding technology and robotics has fostered a wide usage of welding robots in the manufacturing industry: the most popular and common example is found in the automotive industry. Welding robots have in many cases taken over traditional manual welding, which requires a skilled operator and exposes him to an hazardous environment (Tarn et al. 2007). The first step to the automation of robotic welding has been performed by introducing the on-line teaching method (Dilthey and Stein 1993), which is also referred to as teaching and playback, since according to this paradigm the robot just repeats a process learnt after a human-guided teaching process. Such method is however not suited to any change of working conditions, which can significantly affect the outcome of the welding operation (Chen and Lv 2014). Manually teaching from a teaching pendant is also not suited to small production batches, so in all cases in which flexibility and accuracy are requested, or simply the complexity of the operation is too high, an off-line programming of the welding operation is requested.

Programming a robot for welding essentially requires to generate the welding passes, usually from data extracted from a CAD model, and then to generate the associated robot path (Fang et al. 2017). The path is usually developed to enhance productivity, and therefore shorter (i.e., faster) paths are usually sought for, while ensuring obstacle avoidance, which can be obtained using some general-purpose methods (Ogbemhe and Mpofu 2015).

However, welding requires to take into account some specific technical requirements, which mark the difference between general-purpose path planning and welding path planning. In the following, some of these features are recalled and some examples of the related literature are presented.

Joining metal bodies with large gaps requires multiple-pass welding, i.e., the joint must be created by carefully stacking the weld beads according to the best possible geometry. This problem is analyzed in (Zhang et al. 2011), by developing an algorithm to produce optimal paths on the basis of an analytic model of the bead deposition process. The planning of multiple-bead passes are investigated also in (Ahmed et al. 2015), in which the multiple bead passes are planned according to geometry data extracted from a CAD model, and then the transitions between passes are planned for collision-free motion using the A* algorithm. The
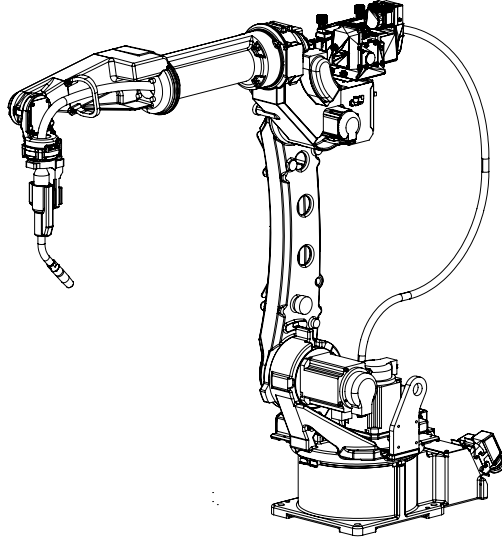
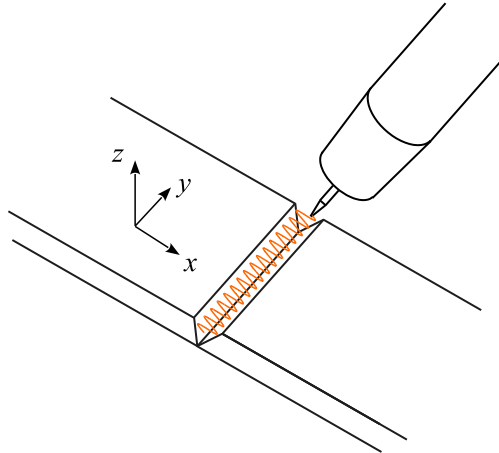Figure 1.6: A six degrees-of-freedom soldering robot.

Figure 1.7: Weave bead welding of a V-groove: planned path.

minimization of the bead number for a faster operation is dealt with in (Yan et al. 2016), which again uses simple analytical descriptions of the bead geometry to produce optimized welding paths.

Another feature of robotic welding that affects path planning is functional redundancy, which arises from the symmetry of the welding torch. Such redundancy can be exploited, as done in the works (Franks et al. 2008; Huo and Baron 2011), to ensure task feasibility when coping with singularity avoidance and joint limits, or for fulfilling a secondary goal.

Another task-specific feature is welding weaving (Chen et al. 2014; Zhan et al. 2017): traditionally it is obtained by adding an oscillating device between the robot flange and the welding torch, but such device is not required when weaving is introduced at the motion planning level, simply by adding a sinusoidal displacement to the end-effector path (Liu et al. 2011; Shi et al. 2015).

A feature than should not be overlooked is that the heat generated during welding introduces some thermal-induced stresses on the material, causing its deformation (Radaj

2012). The usual approach is to minimize the overall distortion by carefully sequencing the beads deposition (Messler Jr 2008), according to the solution of a scheduling optimization problem (Kim et al. 2005). The solution to this scheduling problem is generally obtained through general-purpose optimization routines, among which genetic algorithms seems to be quite popular, as in (Kadivar et al. 2000; Islam et al. 2014), usually defining the fitness function according to a FEM model of the thermal-induced distortions. Alternatively, some heuristics (Kim et al. 1998, 2002) can be used in lieu of a thermo-mechanical model. Some other options for sequencing welding operations are the Ant Colony Optimization and the Particle Swarm Optimization (Tabar et al. 2018; Beik et al. 2019).

1.3   Path planning for spray painting robots

1.3.1   The problem of tool path generation

Nowadays, painting robots are employed in a large number of industrial and manufacturing applications, especially in the automotive, aircraft and furniture manufacturing sectors. The first painting robot was developed by the Norwegian company Tralffa in 1969, and was used for painting wheelbarrows (Gasparetto and Scalera 2019). Since then, the employment of painting machines has been rapidly increasing, thanks to the several advantages of using robots in a paint finishing system (Baldwin 2010). First of all, robots in automation allow to remove humans from hazardous environments, since spray paint particles, if inhaled, can be toxic, carcinogenic, and can lead to chronic neurological problems (Lolin 1989) and pulmonary dysfunctions (Chen et al. 2019c). Furthermore, the spray painting environment is usually noisy, and requires handling bulky paint guns, while performing repetitive tasks. Another feature of automatic painting is the consistency of the results, since a spray painting robot can ensure better performance in terms of repeatability of the resulting surface, paint uniformity and reliability, than the most skilled technician. Furthermore, robot manipulators afford a greater level of system flexibility, allowing facilities to rapidly adapt to changes in the product design. Robotic painting systems ensure the optimization of cycle time and paint waist, and, as a consequence, a reduction of the amount of gaseous polluting emissions (Chen et al. 2017a).

The tool path planning, i.e., the definition of the sequence of positions and orientations of the robot end-effector during the task to ensure a uniform paint distribution is still a challenge in robotic spray painting. Two main approaches can be adopted for the tool path planning: manual and automatic (Chen et al. 2008). In the manual approach an operator manually moves the robot to each desired position, recording the internal joint coordinates corresponding to that end-effector pose (Lozano-Perez 1983). In addition, operations such as activating a spray gun are specified as well. The program is then executed by the robot that moves through the recorded points. This method of robot programming is usually known as *teaching by showing* or *robot guiding*. Similarly, the positions and postures of the robot tool on the processing path against actual work-pieces can be defined by acting on the teaching pendant connected to the robot controller, or by using appropriate external teaching support devices, such as in (Sugita et al. 2004). Manual tool planning can be very time consuming, since the operators usually adopt a trial-and-error approach. With this approach the quality of the results, the cycle time and the paint waist are strictly dependent on the experience

Figure 1.8: An industrial spray painting robot.

and on the skills of the operators. Furthermore, during the execution of the teaching tests the normal production operations must be interrupted.

To overcome these problems, spray painting path and trajectories are usually generated automatically, with an approach called *Computer-Aided Tool path Planning* (CATP) (Chen et al. 2008). This approach is based on the processing of a Computer-Aided Design (CAD) or a point cloud model of the part to be painted, and on the automatic computation of the path and trajectory that the painting robot has to follow. The automatic generation of tool paths avoids trial-and-error operations and reduces the time required to deploy a paint system for a new product, thus reducing production time and costs. However, automatic tool path planning is still a challenging task since the results of the painting process is heavily affected by complex and intertwined factors such as part geometry, the modeling of the spray paint deposition and the flow rate flux of the spray gun. All such information should be included to produce a proper definition of the painting application.

Another important aspect that must be taken into account in the automatic path planning is the compliance with kinematic and dynamic limits of the manipulator. A common approach is to decouple the path definition and the motion law planning into two separate problems (Gasparetto et al. 2012). In this way, the sequence of points that the tool has to follow are defined to ensure a proper covering of the target surface without a specific time law. The motion law, i.e., the speed and acceleration profiles, are then designed by taking into account the specifications and the limits of the manipulator.

In the context of robotic spray painting, recent researches include spray modeling and simulation (Ye and Pulli 2017), automatic path planning (Park and Jeon 2018) and trajectory planning (Trigatti et al. 2018a). Furthermore, robot kinematic and dynamic control (Moe et al. 2018; Zhang et al. 2018), methods for optimizing the base position of mobile painting manipulators (Ren et al. 2016), as well as pose estimation systems (Wang et al. 2019c) are currently being studied. The following subsection introduces the problem of spray painting

modeling, which is a prerequisite for the subsequent definition of the path for the spray painting robot.

1.3.2 *Spray painting modeling*

Spray painting is a complex process, in which paint is transferred to the object surface for protection or aesthetic using air spray as an atomizing medium. Many factors affect the paint flow rate flux through the spray gun and the distribution of spray within the spray cone, which is generally non-uniform. In particular, the most relevant factors that have to be considered are the technical features of the spray gun and paint nozzle, the air pressure, the amount ot thinner in the paint, the temperature of paint and work-piece surface, and the paint viscosity. At present, the mechanism of spray painting is well understood and several models for the flow rate flux and the paint deposition process have been proposed and studied. Most of the paint deposition models consist of analytical functions, which parameters should be determined through fitting repeatable experimental data. These mathematical models usually describe the paint deposition rate on a flat plane with a static spray gun. To account for the painting robot trajectory, the paint thickness is obtained by integrating the paint deposition rate along the path of the spray gun.

Empirical paint deposition models offer a significant advantage over simulation results obtained with numerical methods that usually require complex formulations and high computational costs. Empirical models can also be incorporated into existing simulation tools, providing the user readily available information about the painting process and the characteristics of the resultant coverage path. The main purposes of a deposition model are to capture the structure of the deposition pattern that can be used in a planning system, and to support simulations used to evaluate potential path and trajectory planning algorithms. Indeed, paint deposition models are needed to determine the optimal inter-pass spacing for robotic spray painting, which are the basis of the path planning. These two requirements lead to contradictory criteria, since a deposition model should be accurate enough to predict the paint coverage on different surfaces, but, at the same time, should be mathematically simple and computationally light to be efficiently used within a path planning system. In the deposition process, with *paint coverage* it is usually indicated the total paint thickness on the surface, which depends on the rate of the paint deposition, on the path followed on the surface, and on the speed of the paint gun during the spraying task.

Early approaches to the modeling of spray painting use simplified deposition models, approximating the paint flux of the spray gun with simple analytical functions. These approaches are, in the majority of cases, limited to flat surfaces or make first-order approximations of the surface geometry. For this reason, the utility of these models for the simulation of reliable paint deposition remains limited and restricted to few real applications, such as planar surfaces of automobiles chassis.

Several analytical function are taken into account for the modeling of spray painting. A simple elliptical thickness distribution is considered in the deposition model presented in (Suh et al. 1991), a parabolic thickness profile with a circular deposition pattern is adopted in (Sheng et al. 2000; Chen et al. 2002; Chen and Zhao 2009), whereas in (Freund et al. 1998) a Gaussian distribution with elliptic cross-section is proposed.

Radially symmetric Gaussian distributions of color intensity within the spray cone are
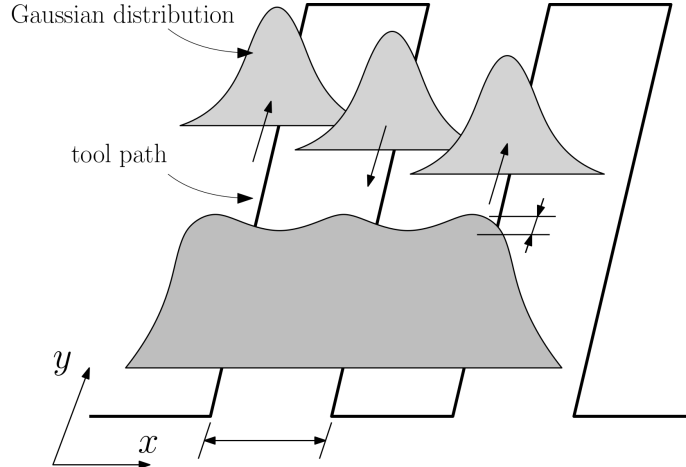
Figure 1.9: Gaussian paint deposition modeling: evaluation of paint thickness uniformity.

considered in the deposition models for decorative robotic spray painting in (Scalera et al. 2017; El Helou et al. 2019; Vempati et al. 2019). Other examples include the deposition model based on a bi-variate Cauchy distribution for the paint deposition applied to a flat panel presented by Ramabhadran and Antonio (Ramabhadran and Antonio 1997), and the model proposed by Balkan and Arikan, based on a beta distribution, which uses the shaping parameter β to take the flow-out of the paint into account (Balkan and Arikan 1999; Sahir Arıkan and Balkan 2000). Furthermore, Hertling et al. propose in (Hertling et al. 1996) a mathematical model for the paint flux field within the spray cone derived from experimental data on flat plates. Results indicate that deposition patterns are not uniform, and not parabolic, as reported by other researchers, but show a minimum at the center of the spray cone.

In the previously described researches the simplified mathematical formulations are developed for aerosol spray painting only. Nevertheless, nowadays, the modern automotive coating lines are increasingly installing electrostatic rotating bell (ESBR) atomizers, which allow one to obtain high transfer efficiency thanks to the potential difference between the rotating bell and the grounded surface to be painted (Conner et al. 2005; Ellwood et al. 2014). ESBR combine electrostatic and aerodynamic effects to spray the charged particles (with a typical diameter of 10-30 μm) to the target surface. Therefore, the mechanism of paint deposition are complex to be investigated and empirically validated analytic models are needed.

Conner et al. presented in (Conner et al. 2005) a paint deposition model that accounts for the deposition pattern of ESRB atomizers and the effects of surface curvature. The deposition pattern is modeled with an asymmetric planar deposition function based on a set of Gaussians, which globally assumes the shape of an asymmetric volcano. The model is tested on primer coated Ford Excursion doors with good results, but presents some limitations in the predictions of paint deposition on highly curved surfaces. In this case, the paint deposition is under-estimated due to electrostatic effects that actually bend the trajectory of the paint droplets back to the edges of the surface.

A limitation of the analytical approach of paint deposition modeling is that sensible errors can be introduced when dealing with curved surfaces. This is due to the assumption that the
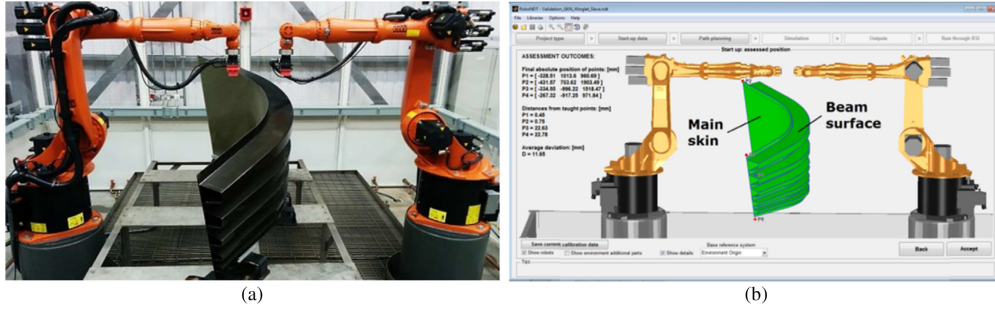
(a)   (b)

Figure 1.10: Spray painting application (a), automatic path generation software (b) (image taken from (Mineo et al. 2017)).

streamlines of paint droplets are straight, unlike the real situation in which the streamlines are curved due to the effects of turbulence in the flow field or due to the shape of the workpiece (Chen et al. 2019a). The problem can be overcame by simulating the paint deposition process with a computational fluid dynamics (CFD) approach, which can precisely describe the flow field and take the turbulence effects into account (Domnick et al. 2005; Fogliati et al. 2006).

1.3.3   Path planning approaches

In the context of robotic spray painting, robot paths are frequently planned through self learning programming. The process can start from the CAD model of the work-piece to be painted, described by means of a parametric model, a tessellated mesh (Sheng et al. 2000; Chen et al. 2008; Zhou et al. 2014), or by a point-cloud model acquired by means of vision or proximity sensors (Gasparetto et al. 2010; Wang et al. 2019c). Several examples of path planning starting from CAD models can be found in the present literature. Early examples are given by (Goodman and Hoppensteradt 1991), where a method for accurate simulation of robotic spray application using empirical parameterization is presented, and by (Asakawa and Takeuchi 1997), where the spray path is first automatically generated on the basis of the CAD data of the work-piece and the spraying parameters, and then converted into robot commands.

The simplest path planning approaches that solve the uniform coverage problem (i.e., to generate a spray path such that the entire surface is completely covered and receives an acceptably uniform layer of paint deposition) take into account single parametric surfaces and are based on the definition of an offset curve. In particular, a start curve (also termed seed curve (Atkar et al. 2003)) is generated on the target surface, then the subsequent paths are built by offsetting the start curve along a family of curves orthogonal to initial one. This approach is implemented in (Atkar et al. 2005b), where the coverage trajectory generation problem is decomposes into three sub-problems: 1) selecting a seed curve, 2) determining a speed profile along each pass, and 3) selecting the spacing between consecutive passes.

The spray deposition can be applied continuously without stopping the paint flow or discontinuously by turning the tool on and off. Several path patterns can be created based on the start curve, such as zigzag, raster, and spiral (Bi and Lang 2007; Chen et al. 2008; Zeng and Ni 2013).

If 3D surfaces are considered instead of planar ones, the path planning become more

complex. A possible strategy is the referred to as 'folding': a 3D model is virtually folded in 2D and treated as a single large surface, then paths are generated in 2D (Hertling et al. 1996). However, this method introduces higher errors as the surface curvature increases.

The path planning on 3D surfaces can also be solved by means of a feature-based approach: each part to be painted is treated through a set of simple features or elementary surface geometries such as planes, cylinders, cavities (regions with negative curvature) and ribs (parallel narrow regions with high curvature). The paths for the robot are then generated for these features individually using predefined strategies for each region (Vincze et al. 2002). Another example of path planning on typical regular surfaces including planes, cylindrical, conical and spherical surfaces can be found in (Zhou et al. 2015). The method is also extended to complex free surfaces with large curvature using hierarchical segmentation to divide the original surface in a number of region to be planned by template programming. The authors in (Kout and Müller 2014) present a general method of offset curve construction with tool-adaptive offsets for free-form surfaces. The offset path is obtained as a family of iso-curves of an anisotropic distance function of a seed curve on the workpiece surface. In (Mineo et al. 2017) a mesh following technique for the generation of tool-paths directly from tessellated models is presented. The technique does not introduce any approximation and allows smoother and more accurate surface following tool-paths to be generated.

Surface segmentation is often used in robotic painting path planning when dealing with complex free-form shapes to divide them into simpler regions (patches). In (Atkar et al. 2005a) the authors showcase the segmentation of a complex automotive surfaces into topologically simple surfaces with a hierarchical procedure using the concept of the watershed segmentation of surfaces (Pulla et al. 2001).

In (Chen et al. 2002; Sheng et al. 2000; Chen and Zhao 2009, 2013; Chen et al. 2017c, 2018, 2019b) the authors adopt a multi-patch approach, in which a CAD model is firstly approximated by a large number of small triangles. The triangles with the nearest locations and directions are then combined into flat patches. For each patch, an approach for flat surface is applied to generate the paths. In (Sheng et al. 2005) tool path planning approach which optimizes the tool motion performance and the thickness uniformity is presented. The method first partitions the part surface into flat patches based on the topology and normal directions, and then determines the movement pattern and the sweeping direction for each patch. Both zigzag and spiral patterns are considered. Zigzag patterns allow simple tool movement, but thier non-isotropic nature introduces makes if difficult to achieve thickness uniformity near the patch borders. Spiral patterns have isotropic nature but they may lead to disconnected path segments for some patch shapes.

In (Bi and Lang 2007) a multi-patch approach is considered, where mesh triangles are sorted to define tag points directly, without the need of sorting triangles into a flat or low-curvature patch. In this manner, the spraying path on complex products such as vehicle chassis can be planned. In (Xia et al. 2009) a surface segmentation based on the determination of the maximum deviation angle of the normal vectors of the vertexes is implemented to generate the patches that are connected and can be covered by paths uniformly. To minimize the cycle time and the material waste, the segmentation also considers as obstacles the holes and the unnecessary painting regions. Furthermore, in (Fu et al. 2017) a genetic algorithm for surface segmentation is presented and two methods are considered: the first is able to separate the largest patch from the surface, whereas the second is capable of dividing the
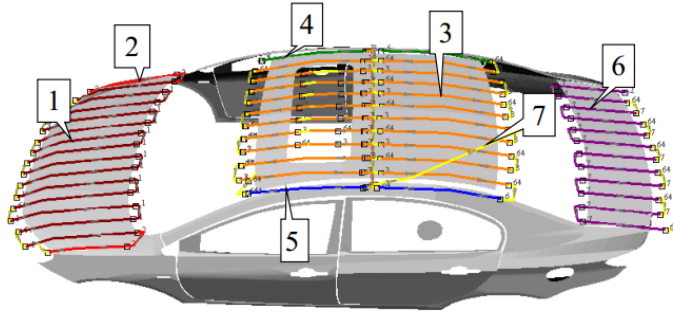
Figure 1.11: Spray painting paths on a car body (image taken from (Chen et al. 2017c)).

surface with the smallest number of slices.

In (Deng et al. 2012), two main methods are identified for the offline path planning of 3D surfaces. In the first approach the CAD mesh file is generated and the robot path is planned by considering the mesh points and the normal vectors to the surface. In the second one, orthogonal planes are used to cut the surface to be coated so as to generate a series of scanning curves. The normal vector is calculated to define the orientation of the torch on every point of the curves. This method is also known as *cutting method* or *marching method* (Bajaj et al. 1988). For example, in (Freitas et al. 2017) radial basis functions are used for surface modeling, and the intersection of surfaces for high-precision trajectory generation. Furthermore, in (Fang et al. 2018) the cutting method is applied to ensure the uniformity of the distance of two neighbor scanning passes in thermal spraying.

Most of the previously referenced works are based on CAD models to plan the robot tool path. However, the path planning can also be based on point cloud models, obtained by means of vision systems or proximity sensors. In (Wang et al. 2015b) a path planning approach based on point cloud slicing is presented. The authors propose an adaptive method to determine the direction of the slicing plane, use polynomial fitting and uniform interpolation method to obtain smooth spray paths, and introduce an iterative formula to optimize the interval between slicing planes.

Another example of path planning approach in which the model of the object to be painted is acquired through artificial vision is given by (Gasparetto et al. 2010). In this work, graph theory and operative search techniques are applied to provide a general and optimal solution to the path planning problem. In particular, the object to be painted is partitioned into primitives that can be represented by a graph and the Chinese Postman algorithm is run on the graph to obtain the minimum-length path covering all arcs.

More recently, in (Wang et al. 2019c), an image of the target is captured using RGB-D vision sensors. The image is then segmented using a segmentation network and processed to estimate the relative pose between the actual target and the pre-scanned target model.

Besides CAD and point-cloud models, other approaches to automatic path planning for painting robots rely on the processing of digital images for artistic purposes. In this case, the path planning can be based on non-photorealistic rendering techniques (Lindemeier et al. 2015; Galea et al. 2016; Scalera et al. 2019; Beltramello et al. 2020), which apply user defined algorithms to render an input image into an artwork, or on deep learning approaches that take an input map of a desired texture, and infer robotic paint commands to produce that

painting (El Helou et al. 2019).

In most of the previous examples the robot path is planned offline. This is due to the fact that offline path planning allows optimization and repeatability of the robot operation, especially when the same task has to be repeated numerous times for many identical pieces, which is a common scenario in the industrial and manufacturing applications.

However, the offline path planning strategy can lead to a decreasing in the spray quality, for example if large-size elements prone to deformation, such as the hull of ships or parts of buildings, are considered. Indeed, in this case, gravity and mechanical deformation would result in inevitable deformations for large-scale parts and possible discrepancies between the as-built workpieces and their nominal specifications would arise (Maset et al. 2020). Thus, the perpendicularity and constancy of distance between subsequent paths computed on the basis of nominal CAD models are not guaranteed, leading to decreased spray quality. Furthermore, in the case of workpiece conveying on the spray-painting pipeline, random pose changes of the part to be painted might occur. To overcome these problems, systems based on the usage of real-time 3-D reconstruction together with online and adaptive path planning techniques are developed. An example of online path planning is given by (Chen et al. 2017b), where the authors adopt a visual feedback based on fringe pattern to control the motion of the robot tool in a closed loop to achieve paint film uniformity. Furthermore, the authors in (Ge et al. 2021) propose an online modeling approach for automatic spray-painting applications. Specifically, two consumer RGB-D cameras are mounted on the two sides of the pipeline, and the data streams of the moving workpiece are continuously collected for the subsequent trajectory planning. Another example of real-time path planning for spray painting purposes is given by (Tadic et al. 2021), where a stereo camera is used for surface recording via a real-time, appearance-based mapping procedure, as well as to steer the painting robot. However, in the online path planning the difficulty on keeping the camera cleaned from paint arises, and more computational resources are needed with respect to the offline scenario to operate both the image acquisition and the path computation in real-time.

The problem of path planning in spray painting robots is usually decoupled from the definition of the motion law that the manipulator has to follow during the execution of the task. The main objective of the trajectory planning is to ensure constant tool speed to minimize the variation of accumulated film thickness on the surface (Antonio 1994). An early example of optimization of the speed profile can be found in (Ramabhadran and Antonio 1997), where two constrained quadratic problems are considered to minimize the painting time subject to lower bounds of speed, and minimize the variation in coating thickness. Nevertheless, these problems do not consider any limit on the end-effector acceleration or any upper bound on end-effector speed. More recently, in (Chen et al. 2019b) not only the spray path defined on a Bezier triangular surface model, but also the end-effector speed along the specified path are optimized to ensure limited variation of the coating thickness.

In (Trigatti et al. 2017, 2018a,b) the authors present a path-constrained trajectory planning strategy that provides feasible motion profiles without resorting to optimization routines and without the need of a dynamic description of the manipulator. The algorithm takes as input an arbitrary description of the end-effector path in the operative space and apply a sequence of look-ahead filtering operations on the speed profile to ensure end-effector speed and joint acceleration limitation.

1.4 Conclusions

In this chapter an overview of the literature on path planning generation in robotics has been presented. The centrality of the problem in robotics is testified by the large number of works written on the topic, which comprises both general-purpose planning methods and application-specific ones. The analysis has been focused on AGVs, medical robots, welding robots and painting robots, as significant examples of the importance of path planning in robotics. In particular, the latter field of application has been analyzed in detail. The analysis has outlined the uttermost importance of path planning in the development of effective robotic operations, as path planning can be used as tool to face the technical challenges of modern industry.

Bibliography

Achour, N., and Chaalal, M. (2011). Mobile robots path planning using genetic algorithms. In *The seventh international conference on autonomic and autonomous systems*, (pp. 111–115).

Ahmed, S. M., Yuan, J., Wu, Y., Chew, C. M., and Pang, C. K. (2015). Collision-free path planning for multi-pass robotic welding. In *2015 IEEE 20th Conference on Emerging Technologies & Factory Automation (ETFA)*, (pp. 1–4). IEEE.

Akai, N., Morales, L. Y., and Murase, H. (2018). Mobile robot localization considering class of sensor observations. In *2018 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, (pp. 3159–3166). IEEE.

Alterovitz, R., Branicky, M., and Goldberg, K. (2008). Motion planning under uncertainty for image-guided medical needle steering. *The International journal of robotics research*, *27*(11-12), 1361–1374.

Antonio, J. K. (1994). Optimal trajectory planning for spray coating. In *Proceedings of the 1994 IEEE international conference on robotics and automation*, (pp. 2570–2577). IEEE.

Asakawa, N., and Takeuchi, Y. (1997). Teachingless spray-painting of sculptured surface by an industrial robot. In *Proceedings of International Conference on Robotics and Automation*, vol. 3, (pp. 1875–1879). IEEE.

Atkar, P. N., Choset, H., and Rizzi, A. A. (2003). Towards optimal coverage of 2-dimensional surfaces embedded in ir/sup 3: choice of start curve. In *Proceedings 2003 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS 2003)(Cat. No. 03CH37453)*, vol. 4, (pp. 3581–3587). IEEE.

Atkar, P. N., Greenfield, A., Conner, D. C., Choset, H., and Rizzi, A. A. (2005a). Hierarchical segmentation of surfaces embedded in r3 for auto-body painting. In *Proceedings of the 2005 IEEE international conference on robotics and automation*, (pp. 572–577). IEEE.

Atkar, P. N., Greenfield, A., Conner, D. C., Choset, H., and Rizzi, A. A. (2005b). Uniform coverage of automotive surface patches. *The International Journal of Robotics Research*, *24*(11), 883–898.

Bae, J., and Chung, W. (2018). A heuristic for path planning of multiple heterogeneous automated guided vehicles. *International Journal of Precision Engineering and Manufacturing*, *19*(12), 1765–1771.

Bailey, T., and Durrant-Whyte, H. (2006). Simultaneous localization and mapping (SLAM): Part ii. *IEEE robotics & automation magazine*, *13*(3), 108–117.

Bajaj, C. L., Hoffmann, C. M., Lynch, R. E., and Hopcroft, J. (1988). Tracing surface intersections. *Computer aided geometric design*, *5*(4), 285–307.

Baldwin, S. (2010). Robotic paint automation: The pros and cons of using robots in your paint finishing system. *Metal Finishing*, *108*(11-12), 126–129.

Balkan, T., and Arikan, M. S. (1999). Modeling of paint flow rate flux for circular paint sprays by using experimental paint thickness distribution. *Mechanics research communications*, *26*(5), 609–617.

Beik, V., Marzbani, H., and Jazar, R. (2019). Welding sequence optimisation in the automotive industry: A review. *Proceedings of the Institution of Mechanical Engineers, Part C: Journal of Mechanical Engineering Science*, *233*(17), 5945–5952.

Beltramello, A., Scalera, L., Seriani, S., and Gallina, P. (2020). Artistic robotic painting using the palette knife technique. *Robotics*, *9*(1), 15.

Bhattacharjee, P., Rakshit, P., Goswami, I., Konar, A., and Nagar, A. K. (2011). Multi-robot path-planning using artificial bee colony optimization algorithm. In *2011 Third World Congress on Nature and Biologically Inspired Computing*, (pp. 219–224). IEEE.

Bi, Z., and Lang, S. (2007). Automated robotic programming for products with changes. *International Journal of Production Research*, *45*(9), 2105–2118.

Broadbent, A., et al. (1987). Free-ranging agv and scheduling system. *Automated guided vehicle systems*, *43*, 301–309.

Cai, C., Sun, C., Han, Y., and Zhang, Q. (2020). Clinical flexible needle puncture path planning based on particle swarm optimization. *Computer Methods and Programs in Biomedicine*, (p. 105511).

Camarillo, D. B., Krummel, T. M., and Salisbury Jr, J. K. (2004). Robotic technology in surgery: past, present, and future. *The American Journal of Surgery*, *188*(4), 2–15.

Candeloro, M., Lekkas, A. M., Hegde, J., and Sørensen, A. J. (2016). A 3d dynamic voronoi diagram-based path-planning system for uuvs. In *OCEANS 2016 MTS/IEEE Monterey*, (pp. 1–8). IEEE.

Castellanos, J. A., and Tardos, J. D. (2012). *Mobile robot localization and map building: A multisensor fusion approach*. Springer Science & Business Media.

Chen, H., Fuhlbrigge, T., and Li, X. (2008). Automated industrial robot path planning for spray painting process: a review. In *2008 IEEE International Conference on Automation Science and Engineering*, (pp. 522–527). IEEE.

Chen, H., Sheng, W., Xi, N., Song, M., and Chen, Y. (2002). Automated robot trajectory planning for spray painting of free-form surfaces in automotive manufacturing. In *Proceedings 2002 IEEE International Conference on Robotics and Automation (Cat. No. 02CH37292)*, vol. 1, (pp. 450–455). IEEE.

Chen, J., Liu, R., Gao, Y., Li, G., and An, T. (2017a). Preferential purification of oxygenated volatile organic compounds than monoaromatics emitted from paint spray booth and risk attenuation by the integrated decontamination technique. *Journal of cleaner production*, *148*, 268–275.

Chen, R., Wang, G., Zhao, J., Xu, J., and Chen, K. (2017b). Fringe pattern based plane-to-plane visual servoing for robotic spray path planning. *IEEE/ASME Transactions on Mechatronics*, *23*(3), 1083–1091.

Chen, S., and Lv, N. (2014). Research evolution on intelligentized technologies for arc welding process. *Journal of Manufacturing Processes*, *16*(1), 109–122.

Chen, W., Chen, Y., Zhang, W., He, S., Li, B., and Jiang, J. (2019a). Paint thickness simulation for robotic painting of curved surfaces based on euler–euler approach. *Journal of the Brazilian Society of Mechanical Sciences and Engineering*, *41*(4), 199.

Chen, W., Liu, H., Tang, Y., and Liu, J. (2017c). Trajectory optimization of electrostatic spray painting robots on curved surface. *Coatings*, *7*(10), 155.

Chen, W., Liu, J., Tang, Y., and Ge, H. (2019b). Automatic spray trajectory optimization on bézier surface. *Electronics*, *8*(2), 168.

Chen, W., Wang, X., Ge, H., and Wen, Y. (2018). Trajectory optimization for spray painting robot on bezier-bernstein algorithm. In *2018 Chinese Automation Congress (CAC)*, (pp. 3389–3394). IEEE.

Chen, W., and Zhao, D. (2009). Tool trajectory optimization of robotic spray painting. In *2009 Second International Conference on Intelligent Computation Technology and Automation*, vol. 3, (pp. 419–422). IEEE.

Chen, W., and Zhao, D. (2013). Path planning for spray painting robot of workpiece surfaces. *Mathematical Problems in Engineering*, *2013*.

Chen, Y., He, Y., Chen, H., Zhang, H., and Chen, S. (2014). Effect of weave frequency and amplitude on temperature field in weaving welding process. *The International Journal of Advanced Manufacturing Technology*, *75*(5-8), 803–813.

Chen, Y.-C., Lin, C.-H., Lung, S.-C. C., Chen, K.-F., Wang, W.-C. V., Chou, C.-T., and Lai, C.-H. (2019c). Environmental concentration of spray paint particulate matters causes pulmonary dysfunction in human normal bronchial epithelial beas-2b cell. *Process Safety and Environmental Protection*, *126*, 250–258.

Conner, D. C., Greenfield, A., Atkar, P. N., Rizzi, A. A., and Choset, H. (2005). Paint deposition modeling for trajectory planning on automotive surfaces. *IEEE Transactions on Automation Science and Engineering*, *2*(4), 381–392.

Connolly, C. I., Burns, J. B., and Weiss, R. (1990). Path planning using laplace's equation. In *Proceedings., IEEE International Conference on Robotics and Automation*, (pp. 2102–2106). IEEE.

Contreras-Cruz, M. A., Ayala-Ramirez, V., and Hernandez-Belmonte, U. H. (2015). Mobile robot path planning using artificial bee colony and evolutionary programming. *Applied Soft Computing*, *30*, 319–328.

Daniels, S. C. (1988). Real time conflict resolution in automated guided vehicle scheduling. Tech. rep., AIR FORCE INST OF TECH WRIGHT-PATTERSON AFB OH.

Davis, J., Perhinschi, M., Wilburn, B., and Karas, O. (2012). Development of a modified voronoi algorithm for uav path planning and obstacle avoidance. In *AIAA Guidance, Navigation, and Control Conference*, (p. 4904).

Dechter, R., and Pearl, J. (1985). Generalized best-first search strategies and the optimality of a. *Journal of the ACM (JACM)*, *32*(3), 505–536.

Dehghan, E., and Salcudean, S. E. (2009). Needle insertion parameter optimization for brachytherapy. *IEEE Transactions on Robotics*, *25*(2), 303–315.

Deng, S., Cai, Z., Fang, D., Liao, H., and Montavon, G. (2012). Application of robot offline programming in thermal spraying. *Surface and Coatings Technology*, *206*(19-20), 3875–3882.

Dilthey, U., and Stein, L. (1993). Robot systems for arc welding-current position and future trends. *Welding Research Abroad*, *39*(12), 2–6.

DiMaio, S. P., and Salcudean, S. E. (2005). Needle steering and motion planning in soft tissues. *IEEE Transactions on Biomedical Engineering*, *52*(6), 965–974.

Domnick, J., Scheibe, A., and Ye, Q. (2005). The simulation of the electrostatic spray painting process with high-speed rotary bell atomizers. part i: Direct charging. *Particle & Particle Systems Characterization*, *22*(2), 141–150.

Duindam, V., Xu, J., Alterovitz, R., Sastry, S., and Goldberg, K. (2009). 3d motion planning algorithms for steerable needles using inverse kinematics. In *Algorithmic Foundation of Robotics VIII*, (pp. 535–549). Springer.

Duinkerken, M. B., Ottjes, J. A., and Lodewijks, G. (2006). Comparison of routing strategies for agv systems using simulation. In *Proceedings of the 2006 winter simulation conference*, (pp. 1523–1530). IEEE.

Durrant-Whyte, H., and Bailey, T. (2006). Simultaneous localization and mapping: part i. *IEEE robotics & automation magazine*, *13*(2), 99–110.

El Helou, M., Mandt, S., Krause, A., and Beardsley, P. (2019). Mobile robotic painting of texture. In *ICRA 2019-IEEE International Conference on Robotics and Automation*.

Elgezua, I., Kobayashi, Y., and Fujie, M. G. (2013). Survey on current state-of-the-art in needle insertion robots: Open challenges for application in real surgery. *Procedia CIrP*, *5*, 94–99.

Ellwood, K. R., Tardiff, J. L., and Alaie, S. M. (2014). A simplified analysis method for correlating rotary atomizer performance on droplet size and coating appearance. *Journal of Coatings Technology and Research*, *11*(3), 303–309.

Englot, B., and Hover, F. (2011). Multi-goal feasible path planning using ant colony optimization. In *2011 IEEE International Conference on Robotics and Automation*, (pp. 2255–2260). IEEE.

Fang, D., Zheng, Y., Zhang, B., Li, X., Ju, P., Li, H., and Zeng, C. (2018). Automatic robot trajectory for thermal-sprayed complex surfaces. *Advances in Materials Science and Engineering*, *2018*.

Fang, H., Ong, S., and Nee, A. (2017). Robot path planning optimization for welding complex joints. *The International Journal of Advanced Manufacturing Technology*, *90*(9-12), 3829–3839.

Farahani, R. Z., Laporte, G., Miandoabchi, E., and Bina, S. (2008). Designing efficient methods for the tandem agv network design problem using tabu search and genetic algorithm. *The International Journal of Advanced Manufacturing Technology*, *36*(9-10), 996–1009.

Fazlollahtabar, H., and Saidi-Mehrabad, M. (2015). Methodologies to optimize automated guided vehicle scheduling and routing problems: a review study. *Journal of Intelligent & Robotic Systems*, *77*(3-4), 525–545.

Fogliati, M., Fontana, D., Garbero, M., Vanni, M., Baldi, G., and Donde, R. (2006). Cfd simulation of paint deposition in an air spray process. *JCT research*, *3*(2), 117–125.

Franks, J., Huo, L., and Baron, L. (2008). The joint-limits and singularity avoidance in robotic welding. *Industrial Robot: An International Journal*.

Fransen, K., van Eekelen, J., Pogromsky, A., Boon, M., and Adan, I. (2020). A dynamic path planning approach for dense, large, grid-based automated guided vehicle systems. *Computers & Operations Research*, *123*, 105046.

Freitas, R. S., Soares, E. E., Costa, R. R., and Carvalho, B. B. (2017). High precision trajectory planning on freeform surfaces for robotic manipulators. In *2017 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, (pp. 3695–3700). IEEE.

23

Freund, E., Rokossa, D., and Roßmann, J. (1998). Process-oriented approach to an efficient off-line programming of industrial robots. In *IECON'98. Proceedings of the 24th Annual Conference of the IEEE Industrial Electronics Society (Cat. No. 98CH36200)*, vol. 1, (pp. 208–213). IEEE.

Fu, Z., Xiao, B., Wu, C., and Yang, J. (2017). A genetic algorithm-based surface segmentation method for spray painting robotics. In *2017 29th Chinese Control And Decision Conference (CCDC)*, (pp. 4049–4054). IEEE.

Galea, B., Kia, E., Aird, N., and Kry, P. G. (2016). Stippling with aerial robots. In *Proceedings of the Joint Symposium on Computational Aesthetics and Sketch Based Interfaces and Modeling and Non-Photorealistic Animation and Rendering*, (pp. 125–134).

Gasparetto, A., Boscariol, P., Lanzutti, A., and Vidoni, R. (2012). Trajectory planning in robotics. *Mathematics in Computer Science*, *6*(3), 269–279.

Gasparetto, A., and Scalera, L. (2019). From the unimate to the delta robot: the early decades of industrial robotics. In *Explorations in the History and Heritage of Machines and Mechanisms*, (pp. 284–295). Springer.

Gasparetto, A., Vidoni, R., Saccavini, E., and Pillan, D. (2010). Optimal path planning for painting robots. In *ASME 2010 10th Biennial Conference on Engineering Systems Design and Analysis*, (pp. 601–608). American Society of Mechanical Engineers.

Ge, J., Li, J., Peng, Y., Lu, H., Li, S., Zhang, H., Xiao, C., and Wang, Y. (2021). Online 3d modeling of complex workpieces for the robotic spray painting with low-cost rgb-d cameras. *IEEE Transactions on Instrumentation and Measurement*.

Geraerts, R., and Overmars, M. H. (2004). A comparative study of probabilistic roadmap planners. In *Algorithmic Foundations of Robotics V*, (pp. 43–57). Springer.

Gonzalez, A. G. C., Alves, M. V. S., Viana, G. S., Carvalho, L. K., and Basilio, J. C. (2018). Supervisory control-based navigation architecture: A new framework for autonomous robots in industry 4.0 environments. *IEEE Transactions on Industrial Informatics*, *14*(4), 1732–1743.

Goodman, E. D., and Hoppensteradt, L. T. (1991). A method for accurate simulation of robotic spray application using empirical parameterization. In *Proceedings. 1991 IEEE International Conference on Robotics and Automation*, (pp. 1357–1368). IEEE.

Hertling, P., Hog, L., Larsen, R., Perram, J. W., and Petersen, H. G. (1996). Task curve planning for painting robots. i. process modeling and calibration. *IEEE Transactions on Robotics and Automation*, *12*(2), 324–330.

Huo, L., and Baron, L. (2011). The self-adaptation of weights for joint-limits and singularity avoidances of functionally redundant robotic-task. *Robotics and Computer-Integrated Manufacturing*, *27*(2), 367–376.

Indri, M., Grau, A., and Ruderman, M. (2018). Guest editorial special section on recent trends and developments in industry 4.0 motivated robotic solutions. *IEEE Transactions on Industrial Informatics*, *14*(4), 1677–1680.

Islam, M., Buijk, A., Rais-Rohani, M., and Motoyama, K. (2014). Simulation-based numerical optimization of arc welding process for reduced distortion in welded structures. *Finite Elements in Analysis and Design*, *84*, 54–64.

Kadivar, M., Jafarpur, K., and Baradaran, G. (2000). Optimizing welding sequence with genetic algorithm. *Computational mechanics*, *26*(6), 514–519.

Kapoor, A., Simaan, N., and Taylor, R. H. (2005). Suturing in confined spaces: constrained motion control of a hybrid 8-dof robot. In *ICAR'05. Proceedings., 12th International Conference on Advanced Robotics, 2005.*, (pp. 452–459). IEEE.

Kavraki, L. E., Svestka, P., Latombe, J.-C., and Overmars, M. H. (1996). Probabilistic roadmaps for path planning in high-dimensional configuration spaces. *IEEE transactions on Robotics and Automation*, *12*(4), 566–580.

Khatib, O. (1986). Real-time obstacle avoidance for manipulators and mobile robots. In *Autonomous robot vehicles*, (pp. 396–404). Springer.

Kim, C. W., and Tanchoco, J. M. (1991). Conflict-free shortest-time bidirectional agv routeing. *The International Journal of Production Research*, *29*(12), 2377–2391.

Kim, C. W., and Tanchocoj, J. (1993). Operational control of a bidirectional automated guided vehicle system. *THE INTERNATIONAL JOURNAL OF PRODUCTION RESEARCH*, *31*(9), 2123–2138.

Kim, D.-W., Choi, J.-S., and Nnaji, B. (1998). Robot arc welding operations planning with a rotating/tilting positioner. *International journal of production research*, *36*(4), 957–979.

Kim, H.-J., Kim, Y.-D., and Lee, D.-H. (2005). Scheduling for an arc-welding robot considering heat-caused distortion. *Journal of the Operational Research Society*, *56*(1), 39–50.

Kim, K.-Y., Norman, B., and Nnaji, B. (2002). Heuristics for single-pass welding task sequencing. *International journal of production research*, *40*(12), 2769–2788.

Kout, A., and Müller, H. (2014). Tool-adaptive offset paths on triangular mesh workpiece surfaces. *Computer-Aided Design*, *50*, 61–73.

Kulatunga, A., Liu, D., Dissanayake, G., and Siyambalapitiya, S. (2006). Ant colony optimization based simultaneous task allocation and path planning of autonomous vehicles. In *2006 IEEE Conference on Cybernetics and Intelligent Systems*, (pp. 1–6). IEEE.

Kwoh, Y. S., Hou, J., Jonckheere, E. A., and Hayati, S. (1988). A robot with improved absolute positioning accuracy for ct guided stereotactic brain surgery. *IEEE Transactions on Biomedical Engineering*, *35*(2), 153–160.

Larsen, L., Kim, J., Kupke, M., and Schuster, A. (2017). Automatic path planning of industrial robots comparing sampling-based and computational intelligence methods. *Procedia Manufacturing*, *11*, 241–248.

Latombe, J.-C. (2012). *Robot motion planning*. vol. 124. Springer Science & Business Media.

LaValle, S. M. (1998). Rapidly-exploring random trees: A new tool for path planning.

Lavallee, S., Troccaz, J., Gaborit, L., Cinquin, P., Benabid, A.-L., and Hoffmann, D. (1992). Image guided operating robot: a clinical application in stereotactic neurosurgery. In *Proceedings 1992 IEEE International Conference on Robotics and Automation*, (pp. 618–619). IEEE Computer Society.

Li, P., Yang, Z., and Jiang, S. (2018). Needle-tissue interactive mechanism and steering control in image-guided robot-assisted minimally invasive surgery: a review. *Medical & biological engineering & computing*, *56*(6), 931–949.

Lindemeier, T., Metzner, J., Pollak, L., and Deussen, O. (2015). Hardware-based non-photorealistic rendering using a painting robot. In *Computer graphics forum*, vol. 34, (pp. 311–323). Wiley Online Library.

Lingelbach, F. (2004). Path planning for mobile manipulation using probabilistic cell decomposition. In *2004 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)(IEEE Cat. No. 04CH37566)*, vol. 3, (pp. 2807–2812). IEEE.

Liu, Y., Zhao, J., Lu, Z., and Chen, S. (2011). Pose planning for the end-effector of robot in the welding of intersecting pipes. *Chinese Journal of Mechanical Engineering-English Edition*, *24*(2), 264.

Lolin, Y. (1989). Chronic neurological toxicity associated with exposure to volatile substances. *Human toxicology*, *8*(4), 293–300.

Louredo, M., Díaz, I., and Gil, J. J. (2012). Dribon: A mechatronic bone drilling tool. *Mechatronics*, *22*(8), 1060–1066.

Lozano-Perez, T. (1983). Robot programming. *Proceedings of the IEEE*, *71*(7), 821–841.

Lulu, L., and Elnagar, A. (2005). A comparative study between visibility-based roadmap path planning algorithms. In *2005 IEEE/RSJ International Conference on Intelligent Robots and Systems*, (pp. 3263–3268). IEEE.

Masehian, E., and Sedighizadeh, D. (2007). Classic and heuristic approaches in robot motion planning-a chronological review. *World Academy of Science, Engineering and Technology*, *23*(5), 101–106.

Maset, E., Scalera, L., Zonta, D., Alba, I., Crosilla, F., and Fusiello, A. (2020). Procrustes analysis for the virtual trial assembly of large-size elements. *Robotics and Computer-Integrated Manufacturing*, *62*, 101885.

Meeran, S., and Share, A. (1997). Optimum path planning using convex hull and local search heuristic algorithms. *Mechatronics*, *7*(8), 737–756.

Messler Jr, R. W. (2008). *Principles of welding: processes, physics, chemistry, and metallurgy.* John Wiley & Sons.

Mineo, C., Pierce, S. G., Nicholson, P. I., and Cooper, I. (2017). Introducing a novel mesh following technique for approximation-free robotic tool path trajectories. *Journal of Computational Design and Engineering*, *4*(3), 192–202.

Moe, S., Gravdahl, J. T., and Pettersen, K. Y. (2018). Set-based control for autonomous spray painting. *IEEE Transactions on Automation Science and Engineering*, *15*(4), 1785–1796.

Mohanty, P. K., and Parhi, D. R. (2016). Optimal path planning for a mobile robot using cuckoo search algorithm. *Journal of Experimental & Theoretical Artificial Intelligence*, *28*(1-2), 35–52.

Nageotte, F., Zanne, P., Doignon, C., and De Mathelin, M. (2009). Stitching planning in laparoscopic surgery: Towards robot-assisted suturing. *The International Journal of Robotics Research*, *28*(10), 1303–1321.

Nguan, C., Girvan, A., and Luke, P. P. (2008). Robotic surgery versus laparoscopy; a comparison between two robotic systems and laparoscopy. *Journal of robotic surgery*, *1*(4), 263–268.

Nguyen Duc, D., Tran Huu, T., and Nananukul, N. (2020). A dynamic route-planning system based on industry 4.0 technology. *Algorithms*, *13*(12), 308.

Ogbemhe, J., and Mpofu, K. (2015). Towards achieving a fully intelligent robotic arc welding: a review. *Industrial Robot: An International Journal*.

Park, K., and Jeon, D. (2018). Optimization of tool path pitch of spray painting robots for automotive painting quality. *International Journal of Control, Automation and Systems*, *16*(6), 2832–2838.

Patil, S., and Alterovitz, R. (2010). Interactive motion planning for steerable needles in 3d environments with obstacles. In *2010 3rd IEEE RAS & EMBS International Conference on Biomedical Robotics and Biomechatronics*, (pp. 893–899). IEEE.

Pulla, S., Razdan, A., and Farin, G. (2001). Improved curvature estimation for watershed segmentation of 3-dimensional meshes. *IEEE Transactions on Visualization and Computer Graphics*, *5*(4), 308–321.

Qiu, L., Hsu, W.-J., Huang, S.-Y., and Wang, H. (2002). Scheduling and routing algorithms for agvs: a survey. *International Journal of Production Research*, *40*(3), 745–760.

Radaj, D. (2012). *Heat effects of welding: temperature field, residual stress, distortion.* Springer Science & Business Media.

Bibliography

Ramabhadran, R., and Antonio, J. K. (1997). Fast solution techniques for a class of optimal trajectory planning problems with applications to automated spray coating. *IEEE Transactions on Robotics and Automation*, *13*(4), 519–530.

Rao, A. M., Ramji, K., and Rao, B. S. S. (2018). Experimental investigation on navigation of mobile robot using ant colony optimization. In *Smart Computing and Informatics*, (pp. 123–132). Springer.

Reed, K. B., Majewicz, A., Kallem, V., Alterovitz, R., Goldberg, K., Cowan, N. J., and Okamura, A. M. (2011). Robot-assisted needle steering. *IEEE robotics & automation magazine*, *18*(4), 35–46.

Ren, S., Xie, Y., Yang, X., Xu, J., Wang, G., and Chen, K. (2016). A method for optimizing the base position of mobile painting manipulators. *IEEE Transactions on Automation Science and Engineering*, *14*(1), 370–375.

Rimon, E., and Koditschek, D. E. (1992). Exact robot navigation using artificial potential functions. *IEEE Transactions on Robotics and Automation, Volume 8*, *8*, 501–518.

Sahir Arıkan, M., and Balkan, T. (2000). Process modeling, simulation, and paint thickness measurement for robotic spray painting. *Journal of Robotic Systems*, *17*(9), 479–494.

Savelsbergh, M., and Sol, M. (1998). Drive: Dynamic routing of independent vehicles. *Operations Research*, *46*(4), 474–490.

Scalera, L., Mazzon, E., Gallina, P., and Gasparetto, A. (2017). Airbrush robotic painting system: Experimental validation of a colour spray model. In *International Conference on Robotics in Alpe-Adria Danube Region*, (pp. 549–556). Springer.

Scalera, L., Seriani, S., Gasparetto, A., and Gallina, P. (2019). Non-photorealistic rendering techniques for artistic robotic painting. *Robotics*, *8*(1), 10.

Sen, S., Garg, A., Gealy, D. V., McKinley, S., Jen, Y., and Goldberg, K. (2016). Automating multi-throw multilateral surgical suturing with a mechanical needle guide and sequential convex optimization. In *2016 IEEE International Conference on Robotics and Automation (ICRA)*, (pp. 4178–4185). IEEE.

Sheng, W., Chen, H., Xi, N., and Chen, Y. (2005). Tool path planning for compound surfaces in spray forming processes. *IEEE transactions on automation science and engineering*, *2*(3), 240–249.

Sheng, W., Xi, N., Song, M., Chen, Y., and MacNeille, P. (2000). Automated cad-guided robot path planning for spray painting of compound surfaces. In *Proceedings. 2000 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS 2000)(Cat. No. 00CH37113)*, vol. 3, (pp. 1918–1923). IEEE.

Shi, L., Tian, X., and Zhang, C. (2015). Automatic programming for industrial robot to weld intersecting pipes. *The International Journal of Advanced Manufacturing Technology*, *81*(9-12), 2099–2107.

Shibata, T., and Fukuda, T. (1993). Intelligent motion planning by genetic algorithm with fuzzy critic. In *Proceedings of 8th IEEE International Symposium on Intelligent Control*, (pp. 565–570). IEEE.

Shirazi, B., Fazlollahtabar, H., and Mahdavi, I. (2010). A six sigma based multi-objective optimization for machine grouping control in flexible cellular manufacturing systems with guide-path flexibility. *Advances in Engineering Software*, *41*(6), 865–873.

Song, J. S. L. X. B., and Zhiyong, Y. (2010). The potential field-based trajectory planning of needle invasion in soft tissue [j]. *Journal of Biomedical Engineering*, *4*.

Song, P.-C., Pan, J.-S., and Chu, S.-C. (2020). A parallel compact cuckoo search algorithm for three-dimensional path planning. *Applied Soft Computing*, (p. 106443).

Sugita, S., Itaya, T., and Takeuchi, Y. (2004). Development of robot teaching support devices to automate deburring and finishing works in casting. *The International Journal of Advanced Manufacturing Technology*, *23*(3-4), 183–189.

Suh, S.-H., Woo, I.-K., and Noh, S.-K. (1991). Development of an automatic trajectory planning system (atps) for spray painting robots. In *Proceedings. 1991 IEEE International Conference on Robotics and Automation*, (pp. 1948–1955). IEEE.

Tabar, R. S., Wärmefjord, K., and Söderberg, R. (2018). Evaluating evolutionary algorithms on spot welding sequence optimization with respect to geometrical variation. *Procedia CIRP*, *75*, 421–426.

Tadic, V., Odry, A., Burkus, E., Kecskes, I., Kiraly, Z., Klincsik, M., Sari, Z., Vizvari, Z., Toth, A., and Odry, P. (2021). Painting path planning for a painting robot with a realsense depth sensor. *Applied Sciences*, *11*(4), 1467.

Tarn, T.-J., Chen, S.-B., and Zhou, C. (2007). *Robotic welding, intelligence and automation*. vol. 362. Springer.

Tavakkoli-Moghaddam, R., Aryanezhad, M., Kazemipoor, H., and Salehipour, A. (2008). Partitioning machines in tandem agv systems based on balanced flow strategy by simulated annealing. *The International Journal of Advanced Manufacturing Technology*, *38*(3-4), 355.

Trigatti, G., Boscariol, P., Scalera, L., Pillan, D., and Gasparetto, A. (2018a). A look-ahead trajectory planning algorithm for spray painting robots with non-spherical wrists. In *IFToMM Symposium on Mechanism Design for Robotics*, (pp. 235–242). Springer.

Trigatti, G., Boscariol, P., Scalera, L., Pillan, D., and Gasparetto, A. (2018b). A new path-constrained trajectory planning strategy for spray painting robots. *The International Journal of Advanced Manufacturing Technology*, *98*(9-12), 2287–2296.

Trigatti, G., Scalera, L., Pillan, D., and Gasparetto, A. (2017). A novel trajectory planning technique for anthropomorphic robots with non-spherical wrist. In *49th International Symposium on Robotics ISR 2017*.

Van Den Berg, J., Miller, S., Duckworth, D., Hu, H., Wan, A., Fu, X.-Y., Goldberg, K., and Abbeel, P. (2010). Superhuman performance of surgical tasks by robots using iterative learning from human-guided demonstrations. In *2010 IEEE International Conference on Robotics and Automation*, (pp. 2074–2081). IEEE.

Vempati, A. S., Khurana, H., Kabelka, V., Flueckiger, S., Siegwart, R., and Beardsley, P. (2019). A virtual reality interface for an autonomous spray painting uav. *IEEE Robotics and Automation Letters*, *4*(3), 2870–2877.

Vincze, M., Pichler, A., Biegelbauer, G., Hausler, K., Andersen, H., Madsen, O., and Kristiansen, M. (2002). Automatic robotic spray painting of low volume high variant parts. In *Proceedings of the 33rd ISR (International Symposium on Robotics)*, vol. 7.

Vivaldini, K. C. T., Galdames, J. P. M., Pasqual, T., Sobral, R., Araújo, R., Becker, M., and Caurin, G. (2010). Automatic routing system for intelligent warehouses. In *IEEE International Conference on Robotics and Automation*, vol. 1, (pp. 1–6). Citeseer.

Wang, C., Wang, L., Qin, J., Wu, Z., Duan, L., Li, Z., Cao, M., Ou, X., Su, X., Li, W., et al. (2015a). Path planning of automated guided vehicles based on improved a-star algorithm. In *2015 IEEE International Conference on Information and Automation*, (pp. 2071–2076). IEEE.

Wang, D., Tan, D., and Liu, L. (2018). Particle swarm optimization algorithm: an overview. *Soft Computing*, *22*(2), 387–408.

Wang, G., Cheng, J., Li, R., and Chen, K. (2015b). A new point cloud slicing based path planning algorithm for robotic spray painting. In *2015 IEEE International Conference on Robotics and Biomimetics (ROBIO)*, (pp. 1717–1722). IEEE.

Wang, J., Shang, X., Guo, T., Zhou, J., Jia, S., and Wang, C. (2019a). Optimal path planning based on hybrid genetic-cuckoo search algorithm. In *2019 6th International Conference on Systems and Informatics (ICSAI)*, (pp. 165–169). IEEE.

Wang, L., Kan, J., Guo, J., and Wang, C. (2019b). 3d path planning for the ground robot with improved ant colony optimization. *Sensors*, *19*(4), 815.

Wang, Z., Fan, J., Jing, F., Liu, Z., and Tan, M. (2019c). A pose estimation system based on deep neural network and icp registration for robotic spray painting application. *The International Journal of Advanced Manufacturing Technology*, (pp. 1–15).

Xia, W., Wei, C., and Liao, X. (2009). Surface segmentation based intelligent trajectory planning and control modeling for spray painting. In *2009 International Conference on Mechatronics and Automation*, (pp. 4958–4963). IEEE.

Xiao, J., Michalewicz, Z., Zhang, L., and Trojanowski, K. (1997). Adaptive evolutionary planner/navigator for mobile robots. *IEEE transactions on evolutionary computation*, *1*(1), 18–28.

Xu, J., Duindam, V., Alterovitz, R., and Goldberg, K. (2008). Motion planning for steerable needles in 3d environments with obstacles using rapidly-exploring random trees and backchaining. In *2008 IEEE international conference on automation science and engineering*, (pp. 41–46). IEEE.

Yan, S., Ong, S., and Nee, A. (2016). Optimal pass planning for robotic welding of large-dimension joints with deep grooves. *Procedia CIRP*, *56*, 188–192.

Yang, X., and Wushan, C. (2015). Agv path planning based on smoothing a* algorithm. *International Journal of Software Engineering and Applications (IJSEA)*, *6*(5), 1–8.

Ye, Q., and Pulli, K. (2017). Numerical and experimental investigation on the spray coating process using a pneumatic atomizer: influences of operating conditions and target geometries. *Coatings*, *7*(1), 13.

Yen, J., and Pfluger, N. (1991). Path planning and execution using fuzzy logic. In *Navigation and Control Conference*, (p. 2801).

Yu, J., Li, R., Feng, Z., Zhao, A., Yu, Z., Ye, Z., and Wang, J. (2020). A novel parallel ant colony optimization algorithm for warehouse path planning. *Journal of Control Science and Engineering*, *2020*.

Zeng, Y., and Ni, X. H. (2013). Path optimization of spray painting robot for zigzag path pattern. In *Advanced materials research*, vol. 712, (pp. 2260–2263). Trans Tech Publ.

Zhan, X., Zhang, D., Liu, X., Chen, J., Wei, Y., Zhou, J., and Liu, R. (2017). Comparison between weave bead welding and multi-layer multi-pass welding for thick plate invar steel. *The International Journal of Advanced Manufacturing Technology*, *88*(5-8), 2211–2225.

Zhang, B., Wu, J., Wang, L., Yu, Z., and Fu, P. (2018). A method to realize accurate dynamic feedforward control of a spray-painting robot for airplane wings. *IEEE/ASME Transactions on Mechatronics*, *23*(3), 1182–1192.

Zhang, H., Lu, H., Cai, C., and Chen, S. (2011). Robot path planning in multi-pass weaving welding for thick plates. In *Robotic Welding, Intelligence and Automation*, (pp. 351–359). Springer.

Zhang, Y., Gong, D.-W., and Zhang, J.-H. (2013). Robot path planning in uncertain environment using multi-objective particle swarm optimization. *Neurocomputing*, *103*, 172–185.

Zhou, B., Fang, F., Shao, Z., Meng, Z., and Dai, X. (2015). Fast and templatable path planning of spray painting robots for regular surfaces. In *2015 34th Chinese Control Conference (CCC)*, (pp. 5925–5930). IEEE.

Zhou, B., Zhang, X., Meng, Z., and Dai, X. (2014). Off-line programming system of industrial robot for spraying manufacturing optimization. In *Proceedings of the 33rd Chinese Control Conference*, (pp. 8495–8500). IEEE.