



Review

A Consolidated Review of Path Planning and Optimization Techniques: Technical Perspectives and Future Directions

Faiza Gul ^{1,*}, Imran Mir ^{2,*}, Laith Abualigah ^{3,4,*}, Putra Sumari ⁴ and Agostino Forestiero ^{5,*}

¹ Department of Electrical Engineering, Aerospace & Aviation Campus Kamra, Air University, Islamabad 43570, Pakistan

² Department of Avionics, Aerospace & Aviation Campus Kamra, Air University, Islamabad 43570, Pakistan

³ Faculty of Computer Sciences and Informatics, Amman Arab University, Amman 11953, Jordan

⁴ School of Computer Sciences, Universiti Sains Malaysia, Gelugor 11800, Pulau Pinang, Malaysia; putras@usm.my

⁵ Institute for High Performance Computing and Networking (ICAR), National Research Council of Italy (CNR), via P.Bucci 8-9C, 87036 Rende (CS), Italy

* Correspondence: faiza.gul@aack.au.edu.pk or faizakhan11@rocketmail.com (F.G.); imran.mir@aack.au.edu.pk (I.M.); aligah.2020@gmail.com (L.A.); agostino.forestiero@icar.cnr.it (A.F.)

Abstract: In this paper, a review on the three most important communication techniques (ground, aerial, and underwater vehicles) has been presented that throws light on trajectory planning, its optimization, and various issues in a summarized way. This kind of extensive research is not often seen in the literature, so an effort has been made for readers interested in path planning to fill the gap. Moreover, optimization techniques suitable for implementing ground, aerial, and underwater vehicles are also a part of this review. This paper covers the numerical, bio-inspired techniques and their hybridization with each other for each of the dimensions mentioned. The paper provides a consolidated platform, where plenty of available research on-ground autonomous vehicle and their trajectory optimization with the extension for aerial and underwater vehicles are documented.

Keywords: path planning; ground vehicle; underwater vehicle; UAV; robotics; numerical techniques; bio-inspired techniques; hybridization; non-linearity



check for updates

Citation: Gul, F.; Mir, I.; Abualigah, L.; Sumari, P.; Forestiero, A. A Consolidated Review of Path Planning and Optimization Techniques: Technical Perspectives and Future Directions. *Electronics* **2021**, *10*, 2250. <https://doi.org/10.3390/electronics10182250>

Academic Editor: Marco Vacca

Received: 6 August 2021

Accepted: 3 September 2021

Published: 13 September 2021

Publisher's Note: MDPI stays neutral with regard to jurisdictional claims in published maps and institutional affiliations.



Copyright: © 2021 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

1. Introduction

The 21st century is the century of autonomy, which accounts for the revolutionary turn in science and technology. The first autonomous guided vehicle was introduced in the 1950s when Barrett Electronics of Northbrook devised a trailer truck that can follow a wire on the ground instead of a truck [1]. Advancement in research and commercial technology made it conceivable for UAVs, robots, and their related application to appear in our daily life activities at an unprecedented rate [2,3]. For UAVs, Dull Dirty and Dangerous (DDD) missions [4–11] are the most prominent applications, whereas for robotics, iRobot applications [12] and Self-Driven cars [13] have gained much importance in research area as well as in commercial technology. Such vehicles require autonomous path planning algorithms to be energy/time efficient for their implementation.

The vehicles are equipped with intelligent equipment to localize their position, detect obstacles, and control the motion utilizing suitable navigational techniques to perform navigation tasks. Hence the selection of appropriate navigational techniques is essential for path planning, optimization, and obstacle avoidance. For path planning and motion control of the vehicle, it is envisaged that the vehicle possesses the capability of detecting the obstacle during motion and judge the environment for traveling. So the question becomes, what is expected from such vehicles?

The primary objective of researchers is to develop a real-time autonomous guided vehicle that can travel and can interpret the information gathered from the environment to precisely determine the position and direction towards the goal in both structured

and unstructured (obstacle cluttered) environments [14]. The next objective is to achieve all these tasks with the shortest, safest, and most economical route, which ensures the computational and space complexity without anybody's intervention [15,16].

Traditionally, path planning involves (a) acquiring information from surroundings, (b) localization of current position, and (c) cognitive mapping helps in taking the required decision satisfying algorithm and executing the task [17]. The autonomous guided vehicle research area lies in formulating computational, algorithmic structures that must be applied to hardware structures utilizing minimum resources. By optimization, further enhancement can be made. An efficient path planning technique of autonomous vehicles can reduce search time and minimize the capital investment of autonomous robots. Optimizing autonomous vehicle path planning involves various practical applications, e.g., disaster management, rescue operations, job performance in industries and factories, agriculture, restaurants, homes, and many others. Due to their applicability and diversity, it has gained importance for researchers to explore the various branches. Autonomous vehicles do not need human assistance for their operation. Any autonomous vehicle needs a path planner to determine the next movement in any indoor/outdoor environment. The definition of path planning differs from researcher to researcher [18,19].

2. Scholarly Contributions and Applications

The optimization algorithms for pathfinding for ground robotics [20–24], aerial vehicles [25–27], and underwater vehicles [28,29] includes a wide range of applications. The most well-known applications for autonomous vehicles are obstacle avoidance, path planning, localization, navigation, sensing, and communication, which works on pre-essential maps related to the environment; they also play a vital role in communication relay, aviation industry for surveillance, and loitering dominated missions. However, motion control and path planning problems are considered complex navigation tasks to perform. Path planning involves numerous strategies to determine how a vehicle can reach its destination point safely, guaranteeing that obstacles are avoided [30].

Oceans are considered the vital assets of a human society [31]. Autonomous underwater vehicles have numerous advantages, including payload capacity, depth activity despite their short battery life, and high cost. An AUV is a reliable subsidiary part of a robot [32] because it involves numerous sensors that are not bound by space and time [33].

Minghan Wei et al. [34] studied mobile robotics for indoor applications. The primary concept for energy-efficient navigation involves offline and online navigation. Offline involves relying on previously built maps of the environment, whereas online caters to real-time navigation by building a map of its locality using local information. The authors built the segmented image of the environment using the covariance function for a Gaussian Process (GP)-type representation. In the online navigation process, energy measurements collected during the trajectory formation estimate the surrounding area's energy profiles using GP regression integrated with an A-star algorithm. The validity and feasibility are checked through simulations and experiments, both for practical application purposes. Jeffrey Delmerico et al. [35] have addressed the issue involved in trajectory formation for ground robotics and observation from a flying robot. The proposed idea is designed for disaster sites for the delivery of aid. It involves the active exploration of the surrounding area, where the flying robots map the entire area for optimization to reduce the response time. The authors estimated the terrain map and performed a 3D simulation. The obtained data from the terrain is used to estimate the efficient trajectory for ground robots. The experiment demonstrated efficient results, and performance capabilities proved exceptionally well. Pablo Marin et al. [36] aimed to analyze the performance of trajectory planning based on the Time Elastic Band (TEB) and on the Ackerman model. The software involved is the Robot Operating System (ROS), and the research platform is the iCab (Intelligent Campus Auto-mobile). The modules involved in the trajectory formation proved that the goal can be achieved without collision. The experiments were performed inside the university Carlos

III from the starting point to the goal point without any collision. Table 1 depicts the few robotics parameters mentioned in different studies.

Table 1. Robotic parameters mentioned in different studies.

Control Panel	Sensor	Software	Testing Environment	Source
E-puck robot	IR, VGA camera, Bluetooth	Webots software	Urban	[37]
Pioneer 3-DX	camera	Xilinx, GA-IP FPGA	Laboratory based	[38]
Matlab(ROS system)	–	ROS (SLAM)	Willow Garage map	[39]
Aria P3-DX	–	Saphira software	simple environment	[40]
Pioneer 3-DX robot	sonar	ROS	simple environment	[41]

In [42], the authors presented the survey UAV helicopter for autonomous cargo pickup, which involved deployment and self-tracking. The authors in [43] discussed airborne maritime surveillance for safeguarding national security and sea surveillance. Unmanned Aerial vehicles known as UAVs tend to take off and land and are popularly used in numerous environments. They are often used as drones' targets. Every mission requires subtle path planning and collision avoidance by optimizing a cost function with constraints. The authors Primatesta et al. [44] presented the risk-aware trajectory strategy for UAVs in urban scenarios. The objective is to calculate the shortest path that mitigates the risk to the population. The authors introduced the off-line and on-line modes of the map computation. First, a tentative map is constructed using static information using an ad hoc variant, an A-star algorithm for trajectory planning, and later, the on-line mode utilizes the dynamic map construction for navigation. Rochin et al. [45] introduce the concept of an autonomous control system to navigate the pre-defined target with the help of a UAV. A camera facing down mounted on a UAV continuously searches for the desired target; with the help of the image detection system, it is completed and the target is found, the navigation stops, and the required target specified location is reported back. The authors combined NED (north-West-Down) with relative coordinates position FRU (Front-Right-Up). In the end, 3D simulation is done using Gazebo for real-world implementation. The Naazare et al. [46] exhibited the application of a graph-based path planner on a UAV to avoid restricted areas. The trajectory builds a visibility graph of the environment using GPS information and finds the shortest path utilizing the A-star algorithm. The generated waypoints show the global localization. Furthermore, the trajectory planner can be used to successfully eliminate the difficulty of the manual operation of UAVs around restricted areas under challenging circumstances. Hailong et al. [47] presented the integration of UAVs with UGVs for mapping, exploration, and navigation in the 3D environment. The system decomposes into a fine-mapping layer and an exploration layer. It uses the SLAM model for mapping and navigation. The proposed idea provides optimized trajectory planning and navigation. The integration of fine mapping with exploration is achieved by OctoMap-based volumetric motion planning. The feasibility and effectiveness are verified via simulation and experiments, which depict the tendency to implement UAV and UGV heterogeneously. James C. Kinsey et al. [48] have done a complete extensive review on underwater vehicle system navigation sensors. They further explained the deterministic and stochastic algorithms involved in UAVs. The paper concluded with future remarks and challenges in UAV systems based on their optimal length, vehicle state navigation, and surrounding estimation for the position. They also highlighted the commercial, military, and scientific advantages of the underwater system for practical purposes.

Collision avoidance is also an essential aspect of UAV; different steps involved in collision avoidance are shown in Figures 1 and 2.

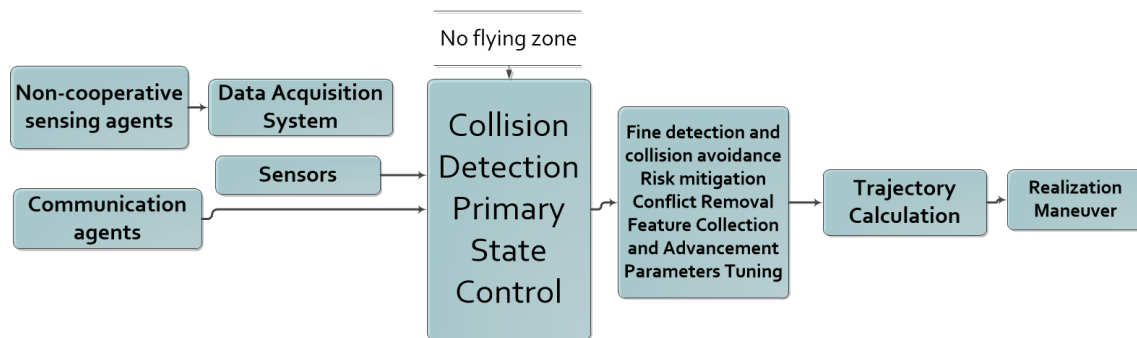


Figure 1. Collision detection steps involve.

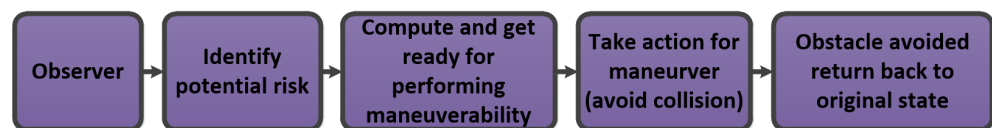


Figure 2. Steps involve in Collision.

The general characterization of trajectory formation of an autonomous vehicle in an environment can be modeled in a three or two-dimensional space, often known as the workspace or search space W . The work/search space contains obstacles, the free path for vehicle maneuverability, an initial position, and a target position. Let W_{oj} be the j th obstacle in the search space and W_{free} be the available space for motion such that $W_{free} = W \cup_j W_{oj}$. Let x_{int} be the initial position of vehicle and y_{goal} be the target position. The following definitions can be deduced:

- i **Definition:** (Trajectory Planning)
Given a function $\partial : [0, M] \rightarrow R^3$ on a bounded variation, where $\partial(0) = x_{int}$ and $\partial(M) = x_{goal}$. If there exists a process ϑ that can retain the values $\partial(\eta) \in W_{free}$, such that for $M \in [0, M]$, then the process is called a continuous process, and ∂ is called trajectory planning.
- ii **Definition:** (Optimal trajectory Planning)
Let optimal trajectory planning have a cost function $C : \Sigma \rightarrow R \geq 0$, such that Σ denotes the set of all paths. If definitions 1 is fulfilled to search the path ∂' and $C(\partial') = \min(C(\partial))$, such that ∂ is a set of all the feasible paths, then ∂' is called as optimal path and ϑ' , and is optimal path planning.

3. Objectives and Content of This Review

The paper extensively evaluates Numerical techniques, Bio-inspired techniques, and their hybridization for popular trajectory planning and obstacle avoidance algorithms available for ground vehicles with the extension for aerial and underwater vehicles in the literature. The paper provides the state-of-the-art background that will enable researchers to work on trajectory optimization and environment modeling. The intent of this paper is to present the comparison of different algorithms and how they can be implemented in different scenarios. The contribution of this review is mentioned below:

- i **Consolidation of relevant work:** The tendency to concurrently discern a vehicle's environment, stabilize and restore its motion, and conduct the required driving maneuvers is an exceptional aptitude of human drivers. All over the world, researchers are working on replicating this maneuverable capability of human drivers into designing an autonomous vehicular system to provide a simplified design, comfort, and safety via ensuring the vehicle efficiency is not perturbed [49–53].
- ii **Exploration of design space and Parametric Characterization through Numerical Solvers:** Numerical solvers are considered the primitive and most predominant tool for determining the design space and modeling the conventional configuration for

ground and aerial vehicles. Few papers on the environment modeling characterization through numerical solvers demonstrate that this area needs to be researched thoroughly. We provide this study in Section 4.

- iii **Survey of trajectory optimization methodologies utilizing Bio-inspired and hybrid Technique:** The selection modus operandi to execute trajectory optimization is the most critical question for computational and numerical studies. The development of numerical techniques for optimization directly relates to the exploration of space for ground and aerial vehicles. The trajectory optimization problem is treated as an optimal non-linear problem, so to formulate the optimal and desired trajectory for ground and aerial vehicles, plenty of optimization methods are present for utilization. Therefore, this urges us to conduct extensive research to highlight the optimization algorithms for performing trajectory optimization. We provide this study in Sections 5 and 6.
- iv **Limitations and the way forward:** The paper's contribution also lies in determining the factors that are not contributing to the optimal trajectory optimization for both ground and aerial vehicles. The drawbacks are categorized into two main areas: (i) the limitations in existing non-linear control techniques; (ii) the limitations in ground and aerial vehicles design. We provide this study at last in Section 7.

Techniques for Path Planning

The path planning and trajectory optimization problem can be solved through numerical techniques, bio-inspired algorithms, and through the hybridization of these techniques with each other.

There are numerous numerical techniques present for determining the exact solution, some of them are: Bisection method [54], Newton Raphson [55] method, Runge Kutta [56], and Iterative method [57]. These methods are further divided into linear algebra equations, spline interpolation, polynomial interpolation, trigonometric interpolation, linear and non-linear programming, and mathematical optimization. These methods can be used for finding any possible solution. For autonomous vehicles, these methods are employed to solve path planning, trajectory optimization, and numerous other vehicle variants.

With growing interest, this research area expanded and introduced bio-inspired techniques to solve trajectory planning, obstacle avoidance, and trajectory optimization. Further, these techniques were utilized on optimizing the path-related issues [58]. The bio-inspired methods are derived from the social hierarchy of birds and animals, which include ants, bees, birds, and genetic algorithms [59–62], after improvement numerous other algorithms have been developed, such as Whale Optimization, Grey Wolf Optimizer, Dragonfly Algorithm, Slap Swarm Algorithm, Grasshopper Algorithm, Ant Lion Optimizer, Moth Flame Optimizer, Simulated Annealing, Deer Hunting Algorithm, Harmony Search Algorithm, and Owl Search Algorithm [63–73].

It is often seen that no one algorithm or technique can guarantee the desired results; therefore, it is common practice to integrate techniques for achieving higher accuracy and designing the system more efficiently. This whole process is called the Hybridization of Algorithms/Techniques [74].

The path planning for autonomous vehicles can further be defined as a multi-objective optimization problem as it requires solving more than one objective, which may involve the generation of suitable trajectories together with obstacles that evade the capability [75]. Based on the ability to perform a task in a surrounding environment, path planning can be categorized into two main categories, namely: (i) the local path planning; (ii) the global path planning, see Figure 3. The former is defined as: if the information of surrounding area is accessible or known to the vehicle before the start of its journey, which is referred to as priori information. Conversely, the latter can be explained as: when the information of the surrounding area is unknown to the vehicle [58,76,77]. Similarly, the environment can also be classified as static or dynamic; when the objects/obstacles are stationary, it is referred to as static, and if the obstacles are in motion, it is referred to as a

dynamic environment [15,17,30,75,76,78]. A few applications related to the ground, aerial, and underwater vehicle systems can be seen in Table 2.

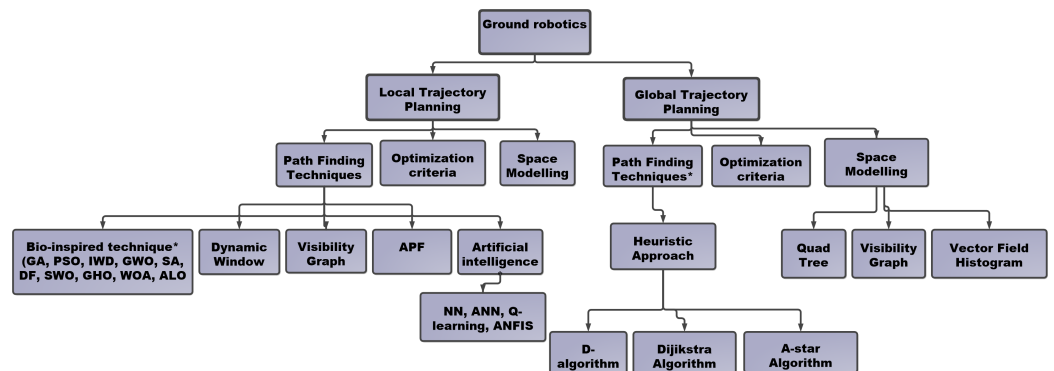


Figure 3. Available Methods for Ground Robotics.

Table 2. Applications involved in different Vehicle System.

	Applications
Ground Vehicle	Agriculture applications of grass cutting, land surveying, soil sampling, precision spraying, weeding, and harvesting of crops, Harvester Robots
Aerial Vehicle	UAV Drones: Mapping and Surveying, Asset Inspection, Mining, Firefighting, Payload carrying, Aviation
Underwater Vehicle	Sea-gliders, Drifters, propeller-driven vehicles

4. Numerical Techniques

The numerical analysis involves the implementation of algorithms for obtaining numerical solutions. It engages the theoretical mathematical analysis. In this section, we present the numerical techniques, numerical optimization software, and their implementation in ground, aerial and underwater vehicles.

Vehicle trajectory optimization is treated as an optimal control problem [9]. Except for simple problems, optimal control problems must be solved numerically. Numerical methods for solving optimal control problems are divided into three methods: indirect methods, direct methods, and dynamic programming [79]. These three methods are then further sub-categorized into different sub-categories, which are graphically depicted in Figure 4 and elaborated in the following section.

- i **Dynamic programming:** Dynamic programming [80] is an optimization approach that transforms a complex problem into a sequence of simpler problems. The optimality criterion in continuous time is based on the Hamilton–Jacobi–Bellman partial differential equation.
- ii **Indirect methods:** In the indirect method [81], the calculus of variations is used to calculate the first-order optimality conditions of the original optimal control problem. The indirect approach solves the problem indirectly by converting the optimal control problem to a boundary-value problem. As a result, the optimal solution is found in an indirect method by solving a system of differential equations that satisfies endpoint and interior-point conditions.
- iii **Direct methods:** In a direct method, the state and control of the optimal control problem are discretized in some manner, and the problem is transcribed to a non-linear optimization problem or non-linear programming problem (NLP). Direct methods are divided into three categories: direct shooting [82], direct multiple shooting [83], and collocation. Direct collocation methods utilize a polynomial approximation to the integrated state equations between the nodes, whereas direct shooting methods

directly integrate state equations. Arguably, the most powerful methods for solving general optimal control problems are direct collocation methods [79]. A direct collocation method is a state and control parameterization method, where the state and control are approximated using a specified functional form. The two most common forms of collocation are local collocation [84] and pseudospectral (global orthogonal) collocation [84]. In optimal control, local collocation has been employed using one of two categories of discretization: Runge–Kutta methods or the orthogonal collocation method [85–87]. In the pseudospectral method [88,89], the optimal control problem is transcribed to a non-linear programming problem (NLP) by parameterizing the state and control using global polynomials (basis function are Chebyshev or Lagrange polynomials) and collocating the differential-algebraic equations using nodes obtained from a Gaussian quadrature. The collocation points are the roots of an orthogonal polynomial (such as Chebyshev or Legendre polynomials) and/or a linear combination of an orthogonal polynomial and its derivatives.

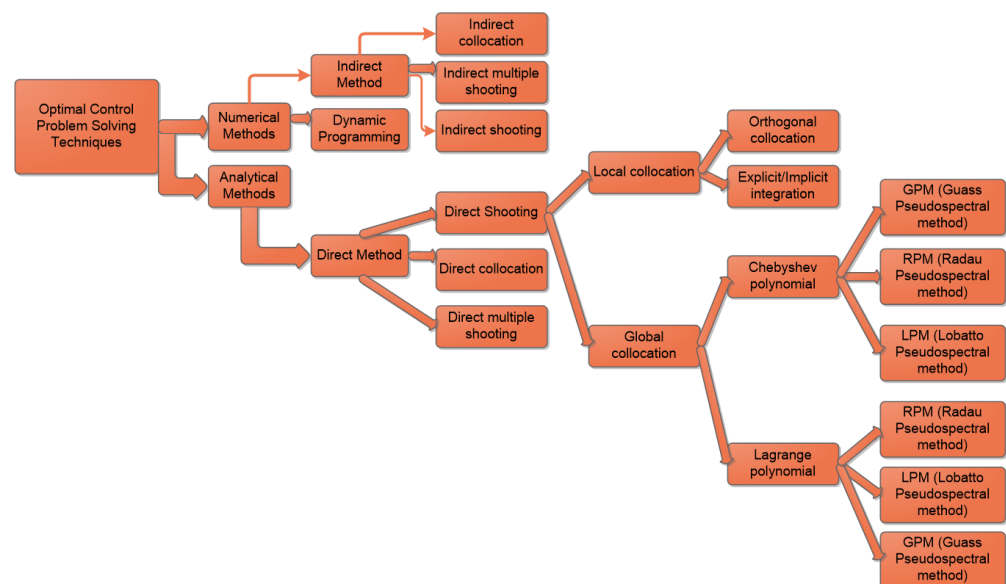


Figure 4. Numerical approaches for the control problem [9].

4.1. Applications to Aerial Vehicles

Researchers utilize different optimal control solvers to determine the optimal trajectories for UAVs in different conditions. Some related work is referenced below:

Using optimal control software, Sachs [90–92] calculated an energy-neutral trajectory. Trajectory finders include Graphical Environment for Simulation and Optimization (GESOP) [93] and Aerospace Launch Trajectory Optimization Software (ALTOS) [94]. ALTOS is an ideal trajectory finder and optimization tool for aeronautical vehicles. This is because, in the presence of multiple local minima, the initial guess might significantly impact the solution’s conclusion. Sachs [95] generated energy-neutral paths for trajectory optimization using two different optimization software: BOUNDSCO and TOMP. The first software, ‘BOUNDSCO’, uses multiple shooting techniques, while the second, ‘TOMP’, uses a parameter optimization strategy to determine optimal control.

Zhao et al. [96,97] used a collocation strategy to turn the optimal control issue into parameter optimization, which they solved numerically with the software Non-linear Programming Solver” (NPSOL) [98]. NPSOL employs a Sequential Quadratic Programming (SQP) technique, where the search direction is a quadratic programming sub-problem solution. The step size is repeatedly chosen at each iteration to create a suitable drop in the augmented Lagrangian merit function. The NPSOL program’s results represent a locally optimal solution to the non-linear programming problem after successful convergence.

Similarly, Akhtar et al. [99,100] implemented path planning using a technique known as Inverse Dynamics in Virtual Domain (IDVD). The non-linear programming problem was solved using Matlab's 'fmincon' to determine feasible paths. Akhtar et al. [101] used a different strategy in another investigation, which was based on Taranenko's direct method. The direct method is a non-linear constrained optimization approach in which the boundary conditions define the reference polynomials. The Pseudo Spectral Optimizer (PSOPT) [102] and Sparse Optimal Control Software (SOCS) are other valuable trajectory optimization software that may be used for dynamic soaring.

Imran Mir et al. [10] presented the integration of dynamic soaring with morphing capabilities for a small Unmanned Aerial Vehicle (sUAV). Variable spans and variable sweeps are two wing morphologies. The non-linear wind gradient profile and 3D point-mass UAV equations of motion have been utilized to model flight dynamics. Parametric characterization has been accessed to check the critical performance parameters for various phases of flight dynamics. The results show that the morphing UAV can perform dynamic soaring in an area where fixed-configuration UAVs might not fall by 15% and 14%. A detailed review of dynamic soaring and non-linear modeling can be found in [9]. Imran Mir et al. [103] presented the integration of wing sweep morphing during the dynamic soaring maneuver. The aerodynamic model is validated using the VLM vortex lattice method, and the trajectory optimization is done using the Gauss pseudospectral method. The performance analysis shows that both the configurations include minimum aerodynamic efficiency and wind shear. Imran Mir et al. [7] researched aerial munitions that can be modeled into smart munitions. The model has a smart adaptation kit (SAK) with a Guidance and Control Module (GCM). The purpose of the kit and GSM is to ensure that SAK glides optimally towards the goal point. The control surfaces were kept at a minimum, which resulted in an actuated system. The paper depicts the application to design a tracking controller for SAK. The results assessed in the simulation using the dynamic model give improved circular error probable (CEP) results. Yu Wu et al. [104] came up with a new consensus theory-based method for formation control and obstacle avoidance in UAVs.

4.2. Applications to Ground Vehicles

The concept started with the DARPA Urban Challenge. Later on, numerous controllers have been developed for dealing with the non-linear characteristics of autonomous vehicles. Different controllers have been designed for autonomous guided vehicles, e.g., PID controller [105], sliding mode controller [106], linear quadratic regulator [107], fuzzy logic controller [108], backstepping controller [109], adaptive control [110], and pure pursuit controller [77]. Some related work from the literature is referenced below:

Thaer et al. [111] studied the robotic arm control parameters with numerical solutions involved with the help of the Runge–Kutta method. The non-linear equations are incorporated with formulas of centrifugal effects, Coriolis, and gravitational torques. The method employed was an attempt to mitigate the error involved in the industrial robotic arm, which helps in the increased production system. The acquired results validate the effectiveness of the numerical method and help in analyzing the variations in position and velocity joints. The Runge–Kutta method output perfectly matches with actual velocities. PeiJiang et al. [112] used a backpropagation algorithm for the path planning solution in the autonomous robot. The path solution is presented by the numerical method. The concept is employed on the robotic arm manipulator. The industrial robot used for this purpose is the KUKA KR 210 R2700 EXTRA robot. Experiments are performed for validating the path tracking. The mean absolute error for a position is also presented. A comparison between the numerical solution based on the Newton–Raphson algorithm and the path planning solution demonstrates the high-end accuracy and efficiency of the path planning solution. Anirudha et al. [113] designed a stability controller by the use of a sums of squares set defined in Lyapunov inequalities. The proposed polynomial controller can be used for handling time-variant dynamics resulting from oscillations involved in trajectory formation. The approach is implemented on an under-actuated double pendulum (Acrobat) and

validates that the proposed method performs efficiently. Azali et al. [114] solve the path planning issue iteratively using the numerical method. The Laplace equation is used to calculate the potential function. The author came up with a block iterative method known as 4 Point-EG to resolve the trajectory planning. The experiment shows that the proposed method can generate a clear path from the start to the goal position and validates that 4 Point-EG works better compared to previous methods involved in trajectory formation.

Evan Kerl et al. [23] presented the PSO algorithm for developing a collision-free path for the autonomous guided vehicle. Then the Gazebo simulator was used to check the response under the ENVI vector representing a solution to the optimization problem. Janine Thoma et al. [22] have summarized images as a set of landmarks, which meet the requirements for image-based navigation. The authors formulated the requirements and divided them into two tasks: accurate self-localization and compact map construction. These particular requirements were then further exploited for a network flow problem related to path planning. Jianhua Li et al. [115] presented the control strategy for trajectory formation by avoiding obstacles. The control approach has two controllers: (i) the controller's map trajectory of the environment and (ii) the obstacle avoidance controller, which helps evade them using vector relationships between the obstacles and the robot. Later, the two controllers combined to perform switching tasks. The Lyapunov function checks the stability of the controller. The simulation results prove that the proposed scheme applied to the trajectory formation of mobile robots guarantees safe maneuverability in an unknown environment.

4.3. Application to Underwater Vehicle

The autonomous underwater vehicle system's (AUV) navigation and controllers have achieved the same importance as ground and aerial vehicles. They are also known as ocean vehicle navigation. It is equally important to address the related literature involved in the AUV system.

Similar to ground and aerial vehicles, autonomous underwater vehicles (AUVs) also need path planning to have an optimal path for their navigation. However, due to data transmission, the sensing range, and power constraints, the sea environment is vulnerable to numerous challenges compared to ground and aerial vehicles. When underwater, it is not easy to communicate effectively because of the continuous fluctuating bandwidth channel. This makes path planning of autonomous underwater vehicles a very challenging task. Motion planning can be categorized into path planning and trajectory planning, and the former can be defined as the course points that the vehicle has to travel to reach the destination point, whereas the time required to complete this journey is formally called trajectory planning. Since no global positioning system (GPS) and no external communication are available underwater, it is hard to acquire information with limited power, and thus, it is hard for an AUV to navigate. Primarily three navigation methods have been suggested [116,117]: (i) acoustic navigation, (ii) dead-reckoning and inertial navigation systems, and (iii) geophysical navigation. Based on the literature survey, they can be categorized as 'close-to-bottom navigation', 'close to-surface navigation', and 'navigation in the mid-depth zone'. Figure 5 shows communication between an autonomous underwater vehicle with unmanned aerial-aquatic vehicle (UAAV) for its navigation purpose.

John J. Leonard et al. [116] surveys the problems linked with the navigation for AUVs. The author focused on good and safe navigation techniques associated with data gathering. The primary modes involved in navigation are: (i) geophysical navigation mode, (ii) dead-reckoning and inertial navigation systems mode, and (iii) acoustic navigation. The recent state-of-art is elaborately explained in the paper.

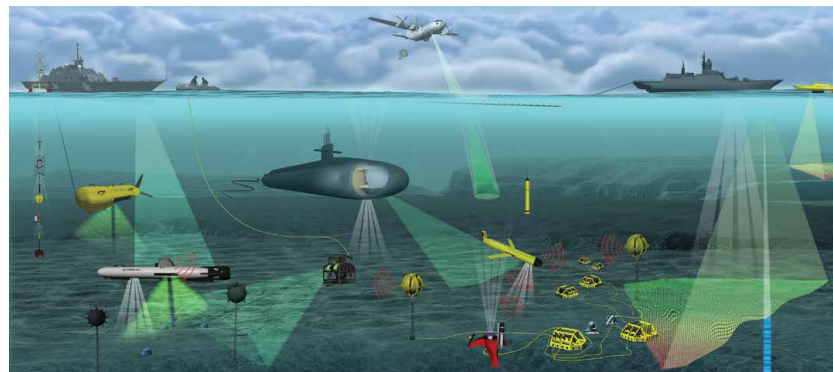


Figure 5. The communication between the autonomous underwater vehicle with the unmanned aerial-aquatic vehicle [118].

John J. Leonard et al. [117] surveys the drawbacks associated with the navigation and trajectory planning involved in AUVs. The non-availability of GPS (Global Positioning System) underwater makes trajectory planning and navigation challenging for research and practical purposes. A recent development has been noticed in this area concerning sensors involvement, and algorithms, such as cooperative navigation and SLAM (simultaneous localization and mapping), have proven to be effective contributory factors involved in AUVs trajectory planning and navigation. Paul A. Miller et al. [119] presented the UAV with 6 degrees of freedom using the error state formulation concept utilized in the Kalman filter. The integration of different sensors has been done to achieve high time propagation and measurement corrections involving gyros, IMU, and accelerometer. The long acoustic baseline (LBL) and Doppler velocity log (DVL), attitude sensor, and pressure sensor aid low rate sensor measurement. A novel coupled technique proposed for integrating DVL and LBL is presented. The LBL is used for estimating correct and accurate error discovery using the transition matrix, whereas high coupled techniques do not involve error estimation as they ignore the error state when used in the measurement cycle. The navigation system allows performing critical sensor calibration to improve system efficiency. The proposed concept is validated in experiments and simulations. V. A. Bobkov et al. [120] proposed the problem associated with autonomous underwater vehicles and 3D reconstruction with the help of stereo images. This process is called odometry. Different modifications are incorporated to maximize accuracy and minimize expenses. This includes an adaptive mode for trajectory calculation.

The paper covers a survey of 3D reconstruction of objects for an underwater vehicle system. Ricardo Pérez-Alcocer et al. [121] proposed a vision-dependent navigation for an autonomous underwater vehicle in a cluttered obstacle environment. A camera mounted on the top of a robotic platform to visually inspect the area is known for aerial and terrestrial applications, but for underwater applications, capturing images is not easy because color can get depleted and blurred out. An adaptive approach for color space in the UAV system is presented to cater to this problem, which can identify features with high visibility. For more excellent stability, a robust free control model is presented. For validation, a real-time experiment is performed. Nak Yong Ko et al. [122] presented a new technique for attitude detection that uses MEMS-AHRS (Micro-electromechanical systems Attitude Heading Reference System). Accurately detecting attitude in real-time is essential for navigation, as trajectory formation and collision avoidance depend on attitude information. An inertial measurement unit (IMU) and three-axis magnetic field are used for attitude detection. The IMU sensor is affected by disturbances, and the magnetic field is affected by EM (electromagnetic field) waves. The authors proposed a depth measurement method whose robustness and accuracy are higher than the magnetic field and IMU sensors, which ultimately improves the efficiency of the attitude estimation. The technique involves quaternion to relate depth with attitude. The proposed method was tested using simulated data and performing different sea trials. The acquired results prove the efficiency of the

proposed method. Talmon Alexandri et al. [123] presented a non-linear navigation solution for UAVs known as Reverse Bearing Only Target Motion Analysis (Reverse BO-TMA). It is a passive method for the localization of UAVs. The proposed idea revolves around bearing measurements of radiated noise from passive vessels sailing around a predefined route. The Reverse BO-TMA remains farther from the reference vessel and does not require integration for the message exchange. The proposed idea incorporates the optimization technique and provides a solution for the least square and unscented Kalman filter. The numerically obtained solutions demonstrate the effectiveness of Reverse BO-TMA for speed and position relative to the Cramer–Rao lower bound. The idea was also validated experimentally in the sea, proving it is suitable for long routes and consumes less energy. Udo Frese et al. [124] exploited the techniques involved in robotics and implemented them for AUVs' navigation. The author studied the development and implementation of different sensors in robotics and applied them to the underwater vehicle system. Because in the underwater system, some spaces are confined and cannot be explored, which means distant environments can be mapped, but these sensors' advantages can be taken. Danhe Chen et al. [125] investigated the unmanned underwater vehicle (UUV) in a complex environment with an inertial navigation system (INU) and a Doppler lag (DL) with an estimation judgment algorithm. The errors occurred due to a deviation in the gyro platform. A linear regulator is incorporated with INS and an adaptive non-linear Kalman filter to mitigate the angles deflections. A regulator was altered at the state-dependent coefficient (SDC), and a modified non-linear Kalman filter was used that was modified through a genetic algorithm. The combined modeling and experiments performed validate the overall efficiency of the proposed idea.

4.4. Summary Numerical Techniques

A summary of numerical techniques involved in aerial, ground, and underwater vehicles are referenced in Table 3 for the speedy convenience of readers.

Table 3. A summary of numerical techniques involved in aerial, ground, and underwater vehicle systems.

Numerical Technique	Contributions	Source
Direct global collocation Pseudo spectral	The author proposed a guidance strategy for autonomous dynamic soaring utilizing Gauss Pseudospectral Optimization Software (GPOPS).	[126–129]
Variable order orthogonal collocation method	Sachs calculated energy-neutral trajectories for trajectory optimization utilizing two other optimization software, namely 'BOUNDSCO' and 'TOMP'. The first program 'BOUNDSCO' is based upon multiple shooting methodology, whereas 'TOMP' is based on a parameter optimization technique for determining optimal control.	[95,130,131]
Graph-based Planner with Visibility Graph	Naazare et al. exhibited a graph-based path planner on a UAV to avoid collision in restricted areas. The trajectory builds a visibility graph of the environment using GPS information and finds the shortest path utilizing the A-star algorithm. The generated waypoints show the global localization. Furthermore, the trajectory planner can be used to successfully eliminate the difficulty of manually operating UAVs around restricted areas under challenging circumstances.	[46,132,133]
Parametric characterization	Imran Mir et al. presented the integration of dynamic soaring with morphing capabilities for a small Unmanned Aerial Vehicle (sUAV). Variable span and variable sweep are two wing morphologies. The non-linear wind gradient profile and 3D point-mass UAV equations of motion have been utilized to model flight dynamics. Parametric characterization has been accessed to check the key performance parameters for various phases of flight dynamics. The results show that the morphing UAV can perform dynamic soaring in an area where fixed-configuration UAVs might not work.	[10,134–136]

Table 3. Cont.

Numerical Technique	Contributions	Source
Runge–Kutta method	Thaer et al. studied the robotic arm control parameters with numerical solutions involved with the help of the Runge–Kutta method. The non-linear equations are incorporated with formulas of centrifugal effects, Coriolis, and gravitational torques. The method employed was an attempt to mitigate the error involved in the industrial robotic arm, which helps in the increased production system. The acquired results validate the effectiveness of the numerical method and help in analyzing the variations in position and velocity joints. The Runge–Kutta method output perfectly matches with true velocities.	[111]
Laplace equation	Azali et al. solve the path planning issue iteratively using a numerical method. The Laplace equation is used to calculate the potential function. The author came up with a block iterative method known as 4 Point-EG for resolving the trajectory planning. The experiment shows that the proposed method can generate a clear path from the start to the goal positions and validates that 4 Point-EG works better as compared to previous methods involved in trajectory formation.	[114]
MEMS-AHRS (Micro-electromechanical systems Attitude Heading Reference System)	Nak Yong Ko et al. presented a new technique for attitude detection that accurately uses MEMS-AHRS for detecting the attitude in real-time. The authors proposed a depth measurement method whose robustness and accuracy are higher than the magnetic field and IMU sensors, which ultimately improves the efficiency of the attitude estimation. The technique involves quaternion to relate depth with attitude. The proposed method was tested using simulated data and performing different sea trials. The acquired results prove the efficiency of proposed method.	[122]

5. Bio-Inspired Methods

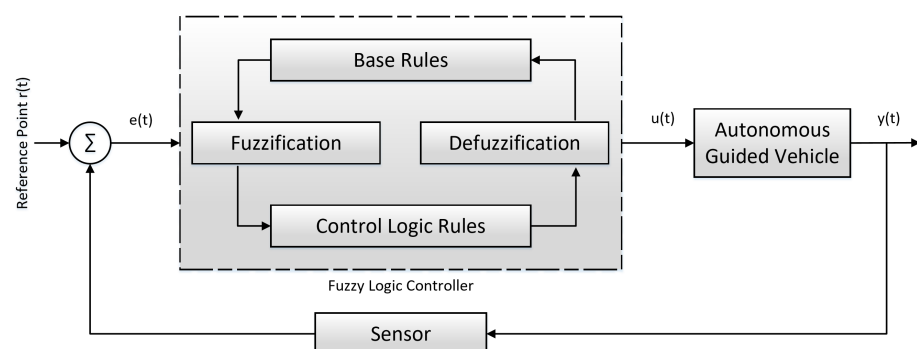
This section contains relevant path planning and trajectory optimization data linked with bio-inspired techniques for ground, aerial, and underwater vehicles.

Siddique et al. [137] studied meta-heuristic and nature-inspired algorithms that imitate natural phenomena of natural sciences. Numerous researchers have addressed the ground and aerial vehicle trajectory planning and obstacle avoidance problem using the optimization algorithm that mimics the behavior of living things, such as fish, ants, bees, whales, wolves, and bats [138–143]. They are known as non-conventional methods. These algorithms are known as bio-inspired techniques and have been utilized in engineering to solve complex mathematical problems in research [144].

Bio-inspired computational-dependent techniques utilized the idea acquired from observing how nature reacts to different things and behaves to solve complex problems, which are considered and characterized with uncertainty and imprecision, to acquire robust solutions at a minimum cost [145]. The most prominent bio-inspired algorithms used in trajectory formation and obstacle avoidance for ground robotics include Artificial Neural Networks (ANN), Fuzzy logic, Genetic Algorithm (GA), Artificial Bee Colony (ABC), Simulated Annealing (SA), etc. The newly established algorithms include the Grey Wolf Optimizer (GWO), Moth Flame Optimization, Whale Optimization Algorithm (WOA), Ant Lion Optimizer (ALO), Dragonfly Algorithm, Grasshopper Optimization Algorithm, and Slap Swarm Algorithm. Bio-inspired algorithms are considered better for performing computational-based navigation for path defining as compared to conventional based algorithms, such as the Artificial Potential Field [146]. Many researchers integrate these non-conventional algorithms with reinforcement learning to increase the performing capability of ground vehicles in a cluttered obstacle environment. Some techniques are mentioned in Table 4 to give insight to the readers.

Table 4. Bio-Inspired Algorithms.

Technique	Seminal Work	Source
Artificial Neural Network	It is based on Kohonen’s self-organizing maps.	[147,148]
Fuzzy Logic	Presented by Professor Lofti Zadeh, in 1965, at the University of California, (refer Figure 6).	[147,148]
Artificial Bee Colony Algorithm	Proposed by Karaboga, in 2005, for solving optimization problems. The algorithm mimics the bees colony behavior for the food search. They are divided into three groups: (i) employed bees, (ii) onlooker bees, and (iii) scouts.	[149–151]
Genetic Algorithm	Derived from evolutionary algorithms, they involve different operators, e.g., mutation, crossover, and selection operator (refer to Figure 7).	[152–160]
Simulated Annealing	It is a probabilistic method used for finding the global minimum of a function. It is considered the first metaheuristic algorithm inspired by the physical phenomena happening in the solidification of fluids, such as metals.	[161]
Grey Wolf Optimizer	Assessing the nature of wolves, researchers were able to formulate mathematical expressions revealing their social behavior in terms of hierarchy distribution of roles in a pack, hunting, the search for prey, and attacking strategies.	[64,162]
Moth Flame Optimization	Inspired by the behavior of moths in nature, its popularity lies in its simple implementation and no derivation involvement in the starting phase with fewer parameters, making it easy to implement and flexible for all kinds of applications.	[69,163]
Whale Optimization	The hunting behavior hierarchy of whales inspires Whale Optimization. They out-stand because of their hunting strategy. Their foraging behavior is called the bubble-net feeding method.	[63,164,165]
AntLion Optimizer	The life cycle of antlions includes two main phases: larvae and adult. Antlions undergo metamorphosis in a cocoon to become adults. They mostly hunt in larvae, and the adulthood period is for reproduction.	[68]

**Figure 6.** Block diagram of the Fuzzy Logic Controller for an autonomous guided vehicle [58].

5.1. Application to Aerial Vehicles

Jesimar et al. [166] applied a Genetic Algorithm to path planning for UAVs during the emergency landing situation. Path planning uses a mathematical function, which caters to all constraints. Three different path planning approaches are used: the Genetic Algorithm, greedy heuristic approach, and multi-population algorithm. The greedy approach helps determine the quick solution, whereas the genetic algorithm returns a better quality solution, which helps mitigate the computational time. The methods were validated on a huge dataset with different levels of difficulty. Simulations were carried on the FlightGear simulator, where the behavior of UAVs was checked under different wind directions and velocity directions. The overall statistical analysis demonstrates that combining genetic algorithms with a greedy approach is beneficial for the path planning of UAVs.

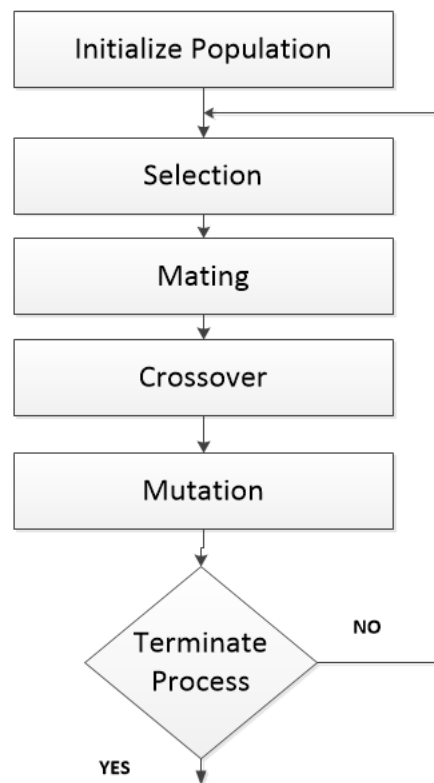


Figure 7. Pseudo-code for the Genetic Algorithm [58].

Zhang et al. [162] also worked on obtaining the optimal flight path by avoiding threats in a combat field. They demonstrated the performance of GWO on an Unmanned Combat Aerial Vehicle (UCAV) for solving path planning in 2D. The UCAV finds the safest route by connecting nodes to reach the desired target by avoiding threats. The results obtained from the simulations were staggering and prove that UCAV is more competent when compared with an evolutionary algorithm. Chengzhi Qu et al. [167] hybridized the algorithms to achieve successful path planning in a UAV. They combined the Grey Wolf Optimizer (GWO) with Symbiotic Organisms Search (SOS) and called it the Simplified Grey Wolf Optimizer (SGWO) and Modified Symbiotic Organisms Search (MSOS), together called HSGWO-MSOS. The exploration and exploitation phases are efficiently combined with speeding up the convergence rate, and the commensalism phase of the SOS algorithm is modified so that it helps in exploitation capability. A linear difference equation is used for analysis purposes, and the cubic B-spline curve method is incorporated to smooth the flight trajectory. The experimental results proved that the proposed algorithm HSGWO-MSOS gives better results, produces feasible outputs, and efficiently performs the flight trajectory. Ram Kishan Dewangan et al. [168] modeled the NP-hard problem as an optimization problem. Finding trajectory for a UAV is problematic as the UAV has to find the path from the start to target points with minimum complexity. The GWO algorithm is implemented to solve the trajectory complexity involved in the UAV. In simulations, the GWO is compared the deterministic algorithms, e.g., D*, Dijkstra, and A* and meta-heuristic algorithms, e.g., Biogeography-Based Optimization (BBO), Whale Optimization Algorithm (WOA), Particle Swarm Optimization (PSO), Intelligent BAT Algorithm (IBA), Sine Cosine Algorithm (SCA), Glowworm Swarm Optimization (GSO), for finding the optimal trajectory for flight. The experimental results show that GWO outperforms the above algorithm in finding the safest trajectory. M.S. Soundarya et al. [169] aim to propose a novel approach for path planning of a UAV along with obstacle avoidance. Path planning is achieved through a swarm intelligence algorithm inspired by the behavior of grey wolves known as

the Grey Wolf Optimizer (GWO). The optimal path planning of UAVs using the GWO is obtained by correctly choosing the objective function for targets and obstacle avoidance conditions. The algorithm has three search agents, alpha, beta, and gamma, which help in the proper convergence of the solution to the target while avoiding obstacles. The proposed approach is tested with different test cases of target and obstacles conditions and reported simulated results. The simulation is carried out in a MATLAB environment.

5.2. Application to Ground Vehicles

Farhad et al. [170] attempted to investigate the neural network technique with statistical dimension reduction techniques to execute the navigation task and obstacle avoidance for the robot. The proposed method uses two feed-forward neural networks with a back-propagation learning algorithm. Laser (SICK) is used with a 180° range to visualize the surrounding environment. The algorithm checks on real-world and experimental results to prove the efficacy of the proposed algorithm. Lingyan Ran et al. [171] worked on vision-based lightweight robot navigation based on uncalibrated spherical images. To improve the trajectory formation, the navigation problem is divided into sub-classification tasks. A 360° fisheye camera is introduced for acquiring spherical images in different heading directions. The classification is accomplished using a Convolutional Neural Network (CNN). The CNN tends to predict paths in different directions with high efficiency. Experimental results prove the validity of the proposed method. Ngangbam Herojit et al. [172] presented the problem related to the navigation of ground robotics and obstacle avoidance with an Artificial Neural Network. The entire area is divided into five segments, then MLP (Multilayer Perceptron) is activated to find the collision-free path. The simulation proves that the said algorithm gives optimal results for reaching the goal position.

M. M. Almasri et al. [173] proposed the multi-robot path planning strategy for static and dynamic obstacles. Eight sensors were incorporated along the robot's sides to gather information from the environment for trajectory formation. The implementation was done in real-time, which validated the proposed algorithm. Akmal et al. [174] developed 256 fuzzy logic rules for a controller, which collects data from the surroundings using an IR sensor. Matlab and Webot Pro are used as software development tools. The controller was implemented in simulations, which validates the results. However, no real-time experiments were implemented, so there is no possible way to judge the approach if constraints are added. Mahmut Dirik et al. [175] proposed the robotic path planning using camera-based on interval type-2 fuzzy logic (IT2FIS). An IT2FIS is used to generate the path and detect obstacles and avoid them to reach the target. Different simulations were performed with differently shaped obstacles to validate the algorithm. The results obtained from the experiments show the efficacy of the proposed strategy. Yupei Yan et al. [176] implemented the fuzzy logic to smooth out the data obtained from the laser sensor. The controller worked best in a dynamic environment and was able to find the trajectory via avoiding obstacles. B.K.Patle et al. [177] presented the new variants of GA, which utilizes binary codes through the matrix for robot path planning navigation (MRN) in a dynamic environment. Trace theory, matrix stimulation, and Sylvester Law of Inertia (SLI) were utilized for establishing a controller. The simulation results presented on MATLAB validates the efficiency of the controller for generating an optimal path. Rath et al. [178] have presented the research on robotic navigation. The authors incorporated a Fuzzy Logic Controller (FL) with GA to solve the trajectory optimization problem. The simulations performed on the proposed method validate the results of the simulation-based 2D ground vehicle. Bakdi et al. [179] presented the two-wheel indoor mobile robot using a Kinect camera system for planning the trajectory. The information acquired from the surroundings is done through the image processing technique, and GA is used for generating an optimal path to join the start position with the target-defined location. Furthermore, to smooth the path, Piecewise Cubic Hermite Interpolating Polynomial is incorporated with GA. At last, an Adaptive Fuzzy Logic Controller is incorporated to keep track of vehicle movements of the left and right wheel velocities. Parallely, the Kinect camera and odometry sensor work to estimate the

current position of the vehicle. The complete proposed integrated concept is implemented on RobuTER to check the feasibility of the algorithm and controller.

Milad Nazarahari [180] presented the novel Artificial Potential Field (APF) to locate all optimal paths between the start and goal positions. An enhanced Genetic Algorithm (EGA) is implemented in the next stage to improve the initial path generation. The EGA uses five mutation and crossover operators. The author deals with three objectives: path smoothness, path distance, and safety—therefore, it is called multi-objective path planning. The authors extended their work on a multi-robot system for trajectory finding. In addition to other objectives, the total distance between all the robots is calculated by adding a new collision removal operator to EGA. Different planar environments of numerous shapes and sizes are added to validate the algorithm to check the computational complexity. The experiments were performed to demonstrate that the proposed method does not affect the control parameters of EGA to a greater extent. At last, the proposed method is experimentally verified by comparing it with different techniques, say, Bi-RRT, A*, Particle Swarm Optimization (PSO), and PRM. The obtained results from the proposed method show that it performs well in terms of computational time, rate, and path length, and when validated on a multi-robot, it creates a collision-free trajectory by finding an optimal feasible solution.

Anh Vu Le et al. [21] discussed the tilting robots with a fixed morphology face in terms of covering the cleaning area and generating the optimal trajectory during navigation. During formulation, the cleaning environment is filled with various tiling patterns of the tetriamond-based robot, and a waypoint addresses each tiling pattern. The objective is to minimize the amount of shape-shifting. The objective function is optimized based on evolutionary algorithms, such as the Ant Colony Optimization (ACO) and Genetic Algorithm (GA) of the Traveling Salesman Problem (TSP), and estimates the shortest path that connects all waypoints. The proposed path planning technique can be extended to other polyiamond-based reconfigurable robots.

Darwish et al. [181] implemented the bees algorithm in real-time path planning. The path is generated in an offline mode, which is later updated using the bees algorithm to avoid collision with obstacles. Amigobot was utilized for evaluating the proposed method, and the results obtained prove the performance of the proposed algorithm in real-time. Jun-Hao et al. [182] proposed a novel design for multi-robot systems without collision. The author presented the ABC algorithm with a modification known as efficient ABC (EABC). The path planning for the multi-robot system chooses the required objective function for obstacle avoidance and reaching the goal safely as required. The elite function is incorporated to enhance the performance metrics of individuals. The simulations performed show the efficacy of the proposed algorithm.

Liu et al. [161] worked in the integration of Simulated Annealing with the Ant Colony Optimization Algorithm to perform the path planning and to solve local optima problems. To further improve the results, the increase entropy strategy was employed. Simulation results prove the efficiency of the proposed algorithm in terms of path planning.

Wu et al. [183] used the approach called Wolf Pack Algorithm (WPA), which is an extension of WCA. It improved the drawbacks involving local optima and efficiency together with two additional rules: (i) the winner wolf takes all generation of a lead wolf, and (ii) the strongest among them survive. The former rules emphasize following the lead wolf, which can be continuously updated through performing iterations. The most muscular wolf survives by following the objective function as fast as possible, ruling out the weakest among the pack. Liu et al. [184] proposed the mathematical model called the Wolf Colony Algorithm (WCA). The method formulates the searching behavior and flank-out the quarry, updating the wolf in the colony using assignment functions. The authors implemented the algorithm on mobile robotics to compute the path length in the least amount of time. The method was compared with GA and PSO. To extract the benefits of nature-inspired algorithm modifications in algorithms is a common practice. Mittal et al. [185] performed the modification by adjusting random parameters of GWO

to achieve the steady-state in exploring the convergence rate associated with the global minima problem. Similarly, Li et al. [186] updated the location of search agents by tuning with weight parameters that help in refining optimal solutions. They called this method a Modified Discrete Grey Wolf Optimizer (MDGWO). Mirjalili et al. [187] presented the novel algorithm for multi-criterion optimization performing Multi-Objective Grey Wolf Optimizer (MOGWO). The objective functions were integrated with the original GWO for selecting the leader and solving non-dominant solutions. The proposed algorithm was tested on different test benchmarks and compared with multi-objective metaheuristics, showing a high convergence speed. Singh et al. [188] worked on the hybridization of the metaheuristics algorithm, which involves the integration of two or more to create a new one. The hybridization of algorithms is often referred to as the H-algorithm. The authors utilize the PSO and GWO in such a way that it increases the exploration of GWO and the exploitation of PSO. The search agents involved in GWO are updated by the inertia and velocity parameters involved in PSO. Muro et al. [189] explained the hunting strategies involved in creating the wolf pack for hunting. The study asserted that the position of search agents involved in hunting is not necessarily important; instead, it deals with the hierarchical division for communication. Rodriguez et al. [190] performed the contradicting conclusion about the hierarchical division and found the new fuzzy hierarchical division in GWO. They came up with three new parameters involved in the implementation of a hierarchical division that affects the positions of alpha, beta, and gamma; they are: (i) fuzzy weights, (ii) weighted average, and (iii) weighted-based on the fitness. The simulations performed on the different benchmark functions show that the added fuzzy weights improved the overall performance of the traditional algorithm.

Seyed Jalali et al. [191] combined the numerical technique called gradient descent, exploiting the neural network, together with the metaheuristic technique called Moth Flame Optimization. The author applied the proposed scheme for finding the trajectory of the mobile robot. The MFO is used for training the multilayer perceptron (MLP) to shadow the problems in the gradient descent. The proposed algorithm is compared with GWO, PSO, MVO, and CS, and the acquired results demonstrate that the integrated technique outperforms. Moreover, the obtained results were also compared with two gradient descent methods called back-propagation (BP) and Levenberg–Marquardt (LM). Seyed Jalali et al. [192] researched different evolutionary algorithms for designing and applying neuroevolution applications. Six different EAs are used for determining the trajectory of the robot, which are the Cuckoo Search (CS), Particle Swarm Optimization (PSO), MultiVerse Optimizer (MVO), Grey Wolf Optimizer (GWO), Moth Flame Optimization (MFO), and Bat Algorithm (BA). A multi-layer perceptron (MLP) network is integrated with all six algorithms, and experiments were conducted using three different datasets. Among all the algorithms, MVO and EA achieve the highest performance metrics.

A complete comprehensive review of Whale Optimization and its applications are discussed in [193]. Thi-Kien Dao et al. [141] presented the multi-objective technique for robot navigation based on the Whale Optimization Algorithm (WOA). Two criteria are fulfilled, i.e., path smoothness and path distance. The proposed algorithm caters to both objectives to plan the trajectory of the robot. The target and start locations are known as the fitness of WOA. The best global whale position is selected in each iteration, which creates waypoints for trajectory formation. The robot updates its position in each iteration with the whale position. The simulation results showed that the proposed algorithm efficiently helps the robot reach the target location within the minimum time. Ankit Chhillar et al. [194] researched trajectory planning and divided it into two methods: (i) the heuristic method and (ii) the classical method. The proposed idea contains the modification of the Whale Algorithm to optimize and create an optimal trajectory. The fitness of the Whale Optimization Algorithm (WOA) depends on the target position and obstacles position in the search area. The proposed idea is verified on simulations and produces a feasible trajectory for a mobile robot.

Zhang Zhenxing et al. [195] utilized the capability of the AntLion Optimizer to search the chaotic space area. In the first step, the population is initialized via utilizing chaotic tent mapping. A self-adaptive dynamic adjustment of the chaotic search is proposed to improve the overall optimization capability and fitness function objectives. A tournament approach is incorporated for picking up the best lion form population. At last, a logistic operator is employed for a random walk of antlions. The analysis was performed on 13 benchmark functions. The obtained data show that the proposed algorithm gives a better convergence rate and is precise. The said algorithm is compared with Artificial Bee Colony (ABC), Grey Wolf Optimizer (GWO), and Particle Swarm Optimization (PSO) and validates the performance in terms of accuracy and speed. Amruta Rout et al. [196] presented the kinematics and dynamics constraints of robotic trajectory. Parameters such as torque and jerks affect the trajectory of robots. Therefore, for smooth path planning, it is required that these parameters be tuned to eliminate the positional error. So to solve this problem, an improved multi-objective AntLion Algorithm is proposed to obtain the optimal trajectory with mitigating the torque and jerk movement rate for a six-axis Kawasaki RS06L industrial robot. The implementation of said algorithm improves the trajectory optimization and reduces the total time involved.

5.3. Application to Underwater Vehicles

Carlos Miguel et al. [197] worked on underwater glider (UWG) vehicles to ensure their mission success and safety. UWG is considered energy-efficient vehicles, and for performing journeys, they are equipped with sensors that collect data from their surroundings. For a safe journey underwater, the vehicles need to maneuver with a low speed and cater to strong ocean waves, which require extensive path planning. Gliders are often involved in multi-objective functions, e.g., shortest path, obstacle avoidance, energy efficiency, etc. The proposed method involves the non-dominated sorting genetic algorithm II (NSGA-II) to support the motion of gliders in a 3D environment. Glider kinematic simulators coupled with NSGA-II were used to perform experiments for controlling multiple control parameters to perform trajectory optimization. The authors were able to configure the parameters for the desired trajectory and proved to perform a real-time experiment in the ocean.

Yan Ma et al. [198] worked on an underwater vehicle system for path planning by improving the traditional Ant Colony Algorithm with Fireworks. In the first step, the Lamb vortex creates a 2D environment model with a random distribution of obstacles; in the second step, a mathematical model is established for calculating time, distance, and energy consumption cost. At last, the Fireworks-Ant Colony Algorithm is employed for solving a non-linear optimization problem. The simulation results obtained from the proposed algorithm compared with the traditional ABC algorithm give improved results and can quickly find an optimal solution.

Lisu Huo et al. [199] worked on path planning and task assignment of multiple UAVs. To effectively balance the task for producing feasible solutions, the author developed the task assignment approach for balancing the UAV's objectives involving an in-flight journey. Virtual nodes are added in the vehicle routing problem (VRP) to obtain temporal constraints results. To simplify and convert temporal-based results into spatial constraints, a Swap-and-Judge Simulated Annealing (SJSa) algorithm is introduced to improve the efficiency of generating feasible solutions. Extensive demonstrations on experiments have been done to procure results for checking the feasibility of the proposed algorithm. The obtained solutions also resolve the combinatorial discrete optimization problems involved in population-based algorithms.

Ni et al. [200], to enhance the computational capability, introduced the neural network target attraction scheme. Xudong et al. [201] incorporated the Ant Colony Optimization technique to simulate the dynamic obstacles and improve the path length.

5.4. Summary Bio-Inspired Techniques

A summary of Bio-inspired techniques involved in aerial, ground, and underwater vehicles are referenced in Table 5 for the speedy convenience of readers.

Table 5. The Impact of the Fuzzy Logic Controller Involved in Aerial and Ground Vehicles.

Method	Contribution	Environment Modeling	Nature Environment	Source
GSA-ACO with two fuzzy logic	Castillo et al. used type-2 fuzzy logic in two different bio-inspired techniques: (i) Gravitational Search Algorithm GSA and (ii) Ant Colony Optimization ACO. The parameters such as elapsed rate and percentage of iterations involved in each of these algorithms are fine-tuned by using a type-2 fuzzy logic controller. By which the behavior of a model can be controlled to perform a local/global search task. To check the feasibility of said controller, benchmark functions are used where fuzzy controllers minimize the error occurring in simulations.	Simulation-based	2D ground vehicle	[202]
Fuzzy Controller	Lagunes et al. works on optimizing a fuzzy controller by using bio-inspired techniques. The inputs used are linear and angular velocity error and torque 1 and 2 to map the desired trajectory. For optimization purposes, the fireflies algorithm is integrated with a fuzzy system.	Simulation-based	2D (ground vehicles)	[203]
SMC Controller	Yu et al. combined two controllers, Sliding Mode Controller and Fuzzy Controller, to regulate the robotic dolphin. The SMC controller checks the line of sight for the robot, and for checking the stability of the algorithm, the Lyapunov function is incorporated to check the convergence properties system. The experimental results show that the said control strategy perfectly steers the mobile robot towards the goal direction.	Simulation-based	2D ground vehicles	[204]
PID and Fuzzy Logic Controller	Soliman et al. presented the comparison of the Omni wheel robot to achieve desire maneuverability. The kinematics model of the mobile robot is implemented on control algorithms, such as PID and Fuzzy Logic Controller. The author tested the proposed integration of controllers on hardware and validated the results obtained from simulations.	Simulation-based	2D ground vehicles	[205]
Fuzzy Logic Controller	Li et al. presented the Fuzzy Logic Controller based on robotic path planning. The referenced location of the obstacle and the formation of the angle between target and robot position are considered input parameters for driving fuzzy control and determining the accurate movement of the mobile robot.	Simulation-based	2D ground vehicles	[206]

6. Hybrid Algorithms

This section presents the relevant data related to hybridized algorithms for path planning and trajectory optimization for ground, aerial, and underwater vehicles.

6.1. Application to Aerial Vehicle

Author Li et al. [207] discussed the engineering problems with the help of the Improved Moth Flame Optimization. The proposed algorithm is implemented on a Levy flight trajectory formation. Harun Ilango et al. [208] presented the comparison of the Moth Flame Optimization, Bats Optimization Algorithm, and Artificial Bee Colony Algorithm for the landing stage involved in UAV. The objective lies in determining the optimal landing path for UAVs in a minimum amount of time. The empirical results obtained from the Moth Flame Optimization Algorithm take less time to find the optimal path than the other algorithms. Rehan Tariq et al. [209] presented the Intelligent Moth Flame Optimization-Based Clustering (IMOC) for drone assistance. The technique is used for maximum coverage using the cluster head approach, which helps find the optimal route. The comparison was made with Ant Colony Optimization (ACO), Grey Wolf Optimization (GWO), and Comprehensive Learning Particle Swarm Optimization (CLPSO). When compared with these algorithms, the proposed algorithm IMOC outperforms the other algorithms in improving the path criterion for UAVs.

Abdelhamied et al. [210] presented the offloading algorithm for UAVs for the execution of intensive tasks. The authors developed two tasks: (i) the air-offloading method and (ii) ground-offloading. The first method, UAV, can offload the computational tasks to surroundings UAVs with available energy resources. The second method involves offloading tasks to an edge cloud server. The proposed method is latency and energy-aware. It selects its execution device based on energy constraints. The simulation results verify the effectiveness of the proposed algorithm.

Haibin Duan et al. [211] proposed the hybrid particle swarm optimization and genetic algorithm (HPSOGA) to solve the multi-UAV optimization problem. The hybridization of algorithms helps in finding time-optimal solutions. The proposed method was then compared with the standard PSO algorithm with a series of experiments to prove the feasibility.

Sotirios Goudos et al. [212] proposed the prediction of received signals (RSS) based on Artificial Neural Networks (ANNs). The data are acquired at multiple altitudes. Then several evolutionary algorithms (EAs) and the Levenberg–Marquardt (LM) backpropagation algorithm for training ANNs and dynamically tuning population size are implemented. The hybrid method was integrated with differential evolution (DE). The training methods obtain better performance to ANN weight, and it exhibits better results. Zhuoning Dong et al. [213] proposed the UAV path re-planning based on the hybrid virtual force and A-star algorithm (HVFA). The formulation of UAV path planning with virtual force is presented. The method is computationally analyzed through simulations.

6.2. Application to Ground Vehicles

Hao Wang et al. [214] presented the integration of the Artificial Neural Network with Fuzzy Logic for path planning. The fuzzy neural network can process data in parallel form and can process fuzzy inference functions according to the need for planning the mobile robotics trajectory. The simulations were performed in an unknown environment with static obstacles. The results obtained from simulations show a fast convergence and high efficiency for finding the optimal path. Pengchao Zhang et al. [215] proposed that the integration of the traditional algorithm with the heuristic programming algorithm based on AI has beneficial results. The traditional rapidly exploring random tree algorithm is incorporated with a neural network to tune path smoothness and path planning functions. The simulations were performed in real-time to check the feasibility of the improved algorithm, which shows the improved results for handling navigation problems. Buddhadeb Pradhan et al. [216] investigates the problem of multi-robots for finding the goal point. Each robot's motion is controlled by the Particle Swarm Optimization, which

the Feeds Forward Neural Network tunes. The coordination algorithm is implemented by a coordinated, cooperative algorithm that maintains the step count of all robots. In the first step, the Artificial Neural Network (ANN) is hybridized with PSO to find the easiest path using acceleration and velocity constraints; the second step, the first and second-order stability analysis, is employed to carry out the convergence. The experiments performed with the proposed algorithm show efficacy and demonstrated promising results. Same as ground vehicles, researchers have also worked on autonomous underwater vehicles.

Faiza et al. [74] also worked on the hybridization of GWO with the PSO algorithm by adding frequency control parameters for GWO. Evolutionary programming was also integrated to smooth out the path for agents involved in searching for prey (food). Simulation results were performed to check the feasibility of the proposed algorithm and validate the algorithm.

Shuguang Zhang et al. [217] worked on the path planning of power, which quickly falls into the local optima problem. To avoid this behavior, a tabu algorithm with simulated annealing coefficients is utilized for redefining the concept of survival of the fittest from the genetic algorithm. This improved version of SA helps in the convergence problem, and the simulation results validate the algorithm's results in different environments.

Asita Kumar Rath et al. [178] presented the research on robotics navigation. The authors incorporated a Fuzzy Logic Controller (FL) with GA to solve the trajectory optimization problem. The simulations performed on the proposed method validate the results. Azzeddine Bakdi et al. [179] presented a two-wheel indoor mobile robot using a Kinect camera system for planning the trajectory. The information acquired from the surrounding is done through the image processing technique, and GA is used for generating an optimal path to join the start position with the target-defined location. Furthermore, to smooth the path, a Piecewise Cubic Hermite Interpolating Polynomial is incorporated with GA. At last, an Adaptive Fuzzy Logic Controller is incorporated to keep track of vehicle movements of the left and right wheel velocities. Parallely, the Kinect camera and odometry sensor work to estimate the current position of the vehicle. The complete proposed integrated concept is implemented on RobuTER to check the feasibility of the algorithm and controller.

Dongshu Wang et al. [218] have presented the enhanced performance of the neural network by refining the training samples using an artificial potential field. They accomplished this task in two steps: (i) defining the global safe area and (ii) dangerous local area. In the safe region, the robot receives the attraction force from the goal and attracts towards it, whereas, in a dangerous area, it receives the repulsive force from obstacles. This repulsive force and angle between the target and obstacle are used as inputs for the fuzzy inferencing system, and the deflection from the robot is taken as output. The final direction taken by the robot is determined by calculating the sum of the deflection angle and direction of attraction force. The coordinates of obstacle and target and the navigation of robot constitute the training samples of neural network. This precise and refined direction acquired from the fuzzy artificial potential field technique gives the neural network an accurate optimization capability to navigate trajectory formation. The simulation and experimental work prove the feasibility of the proposed algorithm.

6.3. Application to Underwater Vehicles

Daqi Zhu et al. [219] have demonstrated the autonomous underwater vehicles (AUV) in two steps by proposing Glasius Bio-inspired Neural Network (GBNN): (i) the construction of a grid map is done via discretization of 2D environment, (ii) then the neural network is constructed on the grid map. At the final stage, a full path is converged using GBNN, and obstacles are avoided using path templates. The simulations show that AUV can fully cover the environment and shows exceptional maneuverability when stuck in a deadlock situation without delay. The results also demonstrate a low overlapping rate with minimum path planning time when using the proposed algorithm.

Sangeeta Kumari et al. [220] proposed a Moth Flame Optimization Algorithm for fault resilient issues in autonomous underwater vehicles (AUVs). Communication is a

great problem in AUVs, so an efficient network is needed to transfer packets towards the base station. A novel fitness function is created for MFO to overcome the failure problem. Performance evaluation shows the effectiveness of the proposed algorithm for AUVs. Wenjie Chen et al. [221] presented the solution to acquire quality images for localization underwater, as already presented algorithms such as SLAM (Simultaneous Localization and Mapping) do not have feature-based extraction quality, which often leads to blurry images. To cater to this issue, a new technique, visual SLAM using Generative Adversarial Networks (GANs), to improve the quality of images by evaluation metrics was introduced. This improves the efficiency of SLAM and provides better localization and accuracy. The proposed method was evaluated on different images using different levels of turbidity in the water. Experiments were carried out on the Raritan River and Carnegie Lake in Princeton, New Jersey, USA.

6.4. Summary of Hybrid Techniques

A summary of few more hybrid techniques involved in aerial, ground, and underwater vehicles are referenced in Table 6 for the speedy conveniences of readers.

Table 6. Impact of Hybrid Methods Involve in Ground and Aerial Vehicles

Contribution	Hybrid Method	Source
Neuro-Fuzzy Method	Many researchers have worked on the obstacle avoidance for mobile robot.	[222–229]
Neuro-Fuzzy Inference System	Authors proposed the adaptive neuro-fuzzy inference system (ANFIS) for ground vehicle navigation and obstacle avoidance. Khepera simulator (KiKs) was used for simulation purposes. Experimental works were done to check the feasibility of the controller.	[230]
Multiple Adaptive Neuro-Fuzzy Inference System	The authors developed the adaptive fuzzy controller with two output parameters and four input parameters. Each adaptive fuzzy controller acts as a single Takagi-Sugeno type fuzzy inference system, where output is the velocity from the left and right wheels, and left and right obstacle distances with heading angle act as input parameters. The robustness of said controller is validated on the simulation platform.	[231]
Hybrid Intelligent System (HIS)	Alves and Lopes proposed the integration of ANN with FL for controlling robot navigation and mitigating the noise production in the system when collecting data from sensors. According to the authors, the integration provides calibration and tuning of parameters not present in the neuro-fuzzy system. Simulations were performed to validate the results successfully.	[232]
Dynamic Self-Generated Fuzzy Q-learning (DSGFQL)	The method was proposed for obstacle avoidance. The method was compared with dynamic fuzzy Q-learning (DFQL) and fuzzy Q-learning (FQL), and the Q-value clustering scheme was compared with the Genetic algorithm. The proposed method is said to produce the desired output and perform well when tested in simulations.	[233–235]

7. Challenges Involved in Path Planning Methods

Though many researchers have studied the path planning for ground, aerial, and underwater vehicles, no algorithm/technique can guarantee 100% results; moreover, the tendency to get stuck in local/global optima or the incapability to judge the obstacle in front may lead to numerous challenges involved with these techniques. These drawbacks significantly affect the performance of the autonomous guided vehicle. Some challenges are mentioned below:

The most used approach for detecting obstacles or planning a path is the deployment of sensors or cameras around any vehicle [236,237]. However, these sensors' readings are neither accurate nor reliable as they are integrated with noise, temperature, and system oscillations, etc. This leads to uncertainty in the system output, which causes unintentional error in the output of the algorithm [238]. The vehicle may produce oscillations and noise, which affect the real-time efficiency related to the data acquired from the environment [239].

Plenty of research has been performed to mitigate and cater the noise occurrence in the vehicle system; however, this is still a challenge. These problems and plenty others widely disturb the implementation of any algorithm in real-time [240]. In vision-based algorithms, the problem lies in identifying pairs of points in the same dimension [241]. This causes ambiguity in identifying points, which results in inconsistent interpretation of any image [242].

Another problem lies in some algorithms that rely on the surrounding environment map for the vehicle to make any decision for navigation. This leads to unnecessary halts in the motion of the vehicle. Baldoni et al. [243] demonstrated this challenge through simulations and shows that the generation of the optimal path for any vehicle is complex, and even if the vehicle reaches the desired destination point, it does not produce smooth navigation.

ANN may have a lot of advantages, as stated earlier, but they require an extensive data set of the surrounding area for the adjustment of hidden layers [244]. The famous backpropagation algorithm has its disadvantages, as it quickly converges to the local minima problem [245]. Table 7 depicts the challenges involved in path planning.

Table 7. Challenges involved in Path Planning.

Cause	Challenges	Source
Sensors/camera	The readings from these sensors are not accurate nor reliable as they are integrated with noise, temperature, and system oscillations, etc. This arises uncertainty in the system output, which causes unintentional error in the output of the algorithm.	[236–238]
Noise occurrence	Plenty of research has been performed to mitigate and cater the noise occurrence in the vehicle system; however, this is still a challenge. These problems and plenty others widely disturb the implementation of any algorithm in real-time.	[240]
Vision-Based	The problem lies in identifying pairs of points in the same dimension. This causes ambiguity in identifying points, which results in inconsistent interpretation of any image.	[241,242]
ANN	This algorithm has numerous advantages, but they require a large data set of the surrounding area for the adjustment of hidden layers. The famous backpropagation algorithm has its own disadvantages, as it easily converges to the local minima problem.	[244,245]

7.1. Proposed Solutions

Trajectory planning is the most researched area in the field of ground vehicles, especially robotics. Numerous deterministic and non-deterministic algorithms are available for solving the trajectory formation. After the DARPA challenge, different algorithms were introduced for path planning (determining shortest path) and obstacle avoidance, namely A*, Dijkstra, APF, PRM, and Rolling window algorithm [246]. Researchers further improved these algorithms and made them compatible for multiple purposes, such as time efficiency. For A* and D*, numerous modifications were done in APF and PRM. However, no single algorithm can provide all the benefits. A significant revival was initiated when nature-inspired algorithms come into play, also known as bio-inspired algorithms; the most prominent algorithms are PSO, ABC, ACO, GWO, WOA, AO, etc. They are designed based on how they behave in nature. Their natural traits are modeled into the form of an algorithm. Developers also modify these algorithms according to the requirements. Motion control is another essential aspect of trajectory finding. Controllers, such as PID, Sliding mode, Linear quadratic regulator, and adaptive control, can also be integrated with a bio-inspired algorithm to enhance the functionality and performance of the vehicle. Because of this, a hybridization, which is the combination of two or more techniques, is used to further aggravate the merits by utilizing the strengths and, at the same time, mitigating the disadvantages and drawbacks of each technique. For example, proper integration of different methods can improve oscillations and reduce noise and data uncertainties due to the local minima problem associated with the APF method [247–249].

7.2. Way Forward

To give the reader insight into possible research areas for trajectory formation and optimization, a bio-inspired technique (Whale Optimizer) is presented integrated with a deterministic method (multi-coordinated robot exploration, CME). The process is called the integration of the deterministic method with the bio-inspired algorithm. Readers may find it interesting to incorporate these methods for space exploration or path planning. Instead of using one robot, the coordination of multiple robots can be employed.

Here, we present the proof of the methodology mentioned above. Using multi-robot(s), exploration of the environment is accomplished utilizing multi-coordinated robot exploration (CME) to evaluate cost values of neighboring cells. We are evaluating every cell for the presence of obstacles so that, while surfing the space, the mobile robots have pre-knowledge of obstacles and can define their track for navigation. Then, the Whale Optimizer is utilized for evaluating the next step of a robot; refer to Figure 8. References can be found in [250]. A possible algorithm for the methodology mentioned above is presented in Algorithm 1, and a possible literature survey is jotted down in Table 8. For a similar approach, another possible direction with the same concept but different optimization technique can be found in [251].

Algorithm 1 Coordinated Multi-robot exploration with WOA.

- 1: Initialize the total number of robots nRbt, initial position (Sp) and iterations (iter), sensor range (SR)
 - 2: **while** t < iter **do**
 - 3: **for** all nRbt **do**
 - 4: Set coordinates of Vc
 - 5: Calculate cost of Vc
 - 6: Perform subtraction, U_j^{sc} and Vc
 - 7: Adjust the frequency function
 - 8: Find best whale (refer to Figure 6 [63])
 - 9: Find leader whale (refer to Figure 6 [63])
 - 10: Find X(t+1), i.e., distance to leader whale
 - 11: Change robot position X(t+1)
 - 12: Reduce the utility value U_j^{sc}
 - 13: **end for**
 - 14: Evaluate Frequency function 'f'
 - 15: **end while**
-

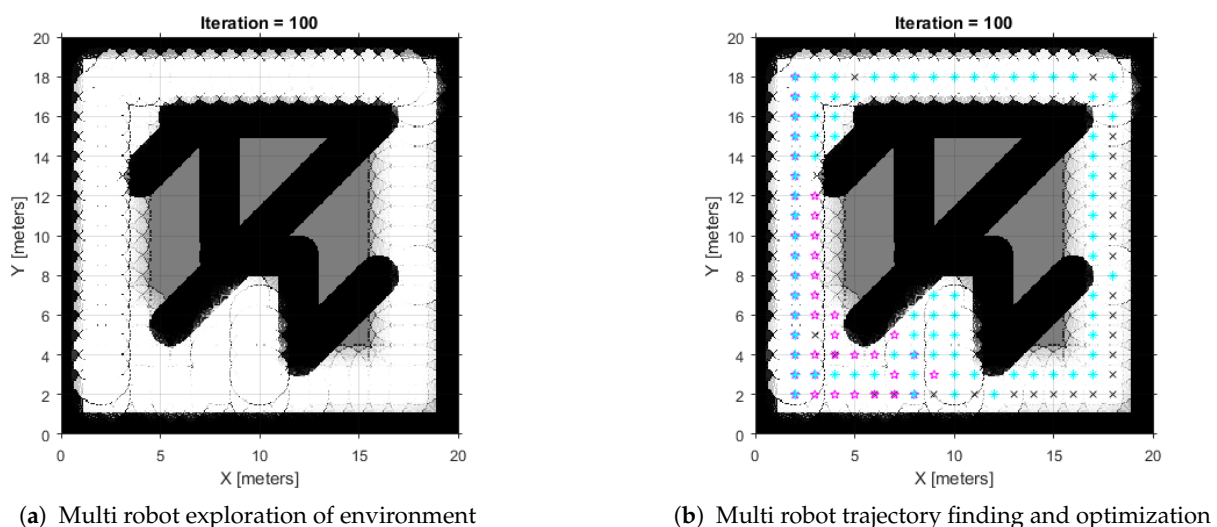


Figure 8. Multi-robot Exploration using Whale Optimization.

Table 8. Literature Survey of all Possible Path Planner.

Approach	Comments	Local/Global	Improvement	Off/On Line	Environment Dimension	Simulation/Experiment
Dijkstra	(a) Low efficiency (b) Robust and efficient success rate	Global/Local	/	off	2D	Simulation
A-star	(a) Low cost (b) Easy implementation and efficient (c) Involves interruption and susceptible to slow convergence	Global/Local	/	off	2D	Simulation
PRM	(a) Precise Results and easy implementation (b) Search path is may not be the optimal path	Global/Local	/	on	2D/3D	Simulation/ Experiment
D-star	(a) Stable (b) Proven effective in obstacle avoidance	Local	/	off	2D	Simulation
D-star-Lite	(a) Fast and Robust (b) Proven effective for dynamic path planning	Local	/	off	2D/3D	Simulation/ Experiment
APF	(a) Simple and easy to implement (b) Fall into local minima problem	Local	Optimization path, improved stability, avoiding local minima	on/off	2D/3D	Simulation/ Experiment

8. Conclusions

Trajectory planning is often required in autonomous vehicles. Over the last decade, a lot of research has been performed to address the strengths and challenges involved in autonomous vehicles. This paper comprehensively discussed and summarized the numerical techniques and optimization techniques involved in ground, aerial, and underwater vehicles. Some strengths and challenges are mentioned in Table 9. The most pertinent conclusion points are summarized as follows:

1. **Consolidation of available information:** A detailed review of the trajectory planning and optimization is presented from the application point of view on ground, aerial, and underwater vehicles. The DARPA challenge 2007 related to robotics, Lord Rayleigh work related to dynamic soaring in 1883, and some extensions related to the underwater vehicle are elaborated. Algorithms, i.e., numerical techniques for implementing the path planning, are discussed.
2. **Survey of trajectory optimization techniques:** A comprehensive overview related to optimization algorithms and numerical techniques that have been utilized for performing trajectory formation and its optimization.
3. **Problem formulation and generation of optimal trajectories:** An explanation of how different algorithms can be integrated to build a mathematical model for planning and the formation of trajectory components can be achieved presented with a literature survey.
4. **Limitations and a way forward:** Though numerous works review robotics, aerial and underwater vehicle systems have been presented together with optimization techniques and numerical methods, and it has been observed no single algorithm produces desired results or accurate output; therefore, a hybridization of different algorithms has been used by researchers. Two optimization algorithms or two numerical methods together can be integrated, or a mix and match of techniques can be achieved for obtaining the desired characteristics results.

Table 9. Strengths and Challenges Involved in Hybrid Methods for Ground & Aerial Vehicles.

Algorithms	Strengths	Challenges	Implementation	Time Complexity
Fuzzy Logic	(a) The fuzzy rules can be tuned for desirable requirement [3] (b) Control logic implementation is easy [252] (c) Can be easily integrated with bio-inspired algorithms [3]	(a) Difficult to create membership functions	Real-time and simulation	$T \geq 0(n^2)$
Neural Network	(a) Works best in real-time (b) Imitate human control logic easily (c) Use of backpropagation results in a local minimum problem [253] (d) Acquiring a large data set in real-time is difficult [244]	(a) Difficult to handle buried neuron layers in the network [244] (b) Increase in layers increases complexity [244]	Real-time and simulation	$T \geq 0(n^2)$
Genetic Algorithm	(a) Faster convergence rate and optimization capability [46] (b) Combine well with other algorithms [46] (c) Because of easy implementation integrate well with other algorithms [181]	(a) Get stuck in local minima problem when environment complexity increase [254] (b) Produce oscillations in system [255]	Simulation	$T \geq 0(n^2)$
ABC	(a) Requires fewer control parameters [151] (b) Requires less computational time [181] (c) Because of easy implementation integrate well with other algorithms [181]	(a) Slow convergence rate [256]	Simulation	$T \geq 0(n^2)$
Simulated Annealing	(a) Good at approximating global optimum [161]	(a) Slow convergence rate [161]	Simulation	$T \geq 0(n^2)$
GWO	(a) Fast convergence rate [183] (b) Lesser variable involvement [183] (c) Easily integrated with other algorithms [184]	(a) Implementation gets tricky when complex scenarios arise [185]	Simulation	$T \geq 0(n^2)$
Moth Flame	(a) Compared to other algorithms, it produces good solutions in complex scenarios [192]	(a) Has premature convergence rate [191]	Simulation	$T \geq 0(n^2)$
WOA	(a) Easy implementation with fast convergence rate [194]	(a) Difficult to handle in a complex environment [141]	Simulation	$T \geq 0(n^2)$
AntLion	(a) Produces good results in complex environment [195]	(a) Involvement of a lot of variables makes it difficult to handle when integrated with different algorithms [74,196]	Simulation	$T \geq 0(n^2)$

Author Contributions: Conceptualization, F.G. and I.M.; methodology, F.G.; software, F.G.; validation, F.G., I.M., L.A. and A.F.; formal analysis, P.S.; investigation, F.G.; resources, F.G.; data curation, F.G., I.M. and L.A.; writing—original draft preparation, F.G.; writing—review and editing, F.G. and L.A.; visualization, F.G., I.M., L.A. and A.F.; supervision, I.M., L.A.; project administration, I.M., L.A.; funding acquisition, A.F. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not Applicable.

Informed Consent Statement: Not Applicable.

Data Availability Statement: Not Applicable.

Conflicts of Interest: The authors declare no conflict of interest.

Abbreviations

The following abbreviations are used in this manuscript:

UAV	Unmanned Aerial Vehicles
AUV	Autonomous Underwater Vehicles
UGVs	Unmanned Ground Vehicles
SLAM	Simultaneous Localization and Mapping
sUAV	Small Unmanned Aerial Vehicle
UAAV	Unmanned Aerial-Aquatic Vehicle
ROS	Robot Operating System
UUV	Unmanned Underwater Vehicle
iCab	Intelligent Campus Auto-mobile
TEB	Time Elastic Band
GP	Gaussian Process
NED	North-West-Down
FRU	Front-Right-Up
NLP	Non-Linear Programming
GESOP	Graphical Environment for Simulation and Optimization
ALTOS	Aerospace Launch Trajectory Optimization Software
IDVD	Inverse Dynamics in Virtual Domain
PSOPT	Pseudo Spectral Optimizer
SAK	Smart Adaption Kit
GCM	Guidance and Control Module
CEP	Circular Error Probable
GPS	Global Positioning System
LBL	Long Base Line
DVL	Doppler Velocity Log
IMU	Inertial Measurement Unit
EM	Electromagnetic Field
MEMS	Micro-Electromechanical Systems
AHRS	Attitude Heading Reference System
RBO-TMA	Reverse Bearing Only Target Motion Analysis
SDC	State-Dependent Coefficient
IN	Inertial Navigation
PSO	Particle Swarm Optimization
GWO	Grey Wolf Optimization
ANN	Artificial Neural Network
GA	Genetic Algorithm
ALO	Ant Lion Optimization
WOA	Whale Optimization
CNN	Convolutional Neural Network
SLI	Sylvester Law of Inertia
NSGA II	Non-dominated sorting genetic algorithm II
UWG	Underwater Glider

References

1. Li, S.; Yan, J.; Li, L. Automated guided vehicle: The direction of intelligent logistics. In Proceedings of the 2018 IEEE International Conference on Service Operations and Logistics, and Informatics (SOLI), Singapore, 31 July–2 August 2018; pp. 250–255.
2. Fanti, M.P.; Mangini, A.M.; Pedroncelli, G.; Ukovich, W. A decentralized control strategy for the coordination of AGV systems. *Control Eng. Pract.* **2018**, *70*, 86–97. [[CrossRef](#)]
3. Zhong, M.; Yang, Y.; Dessouky, Y.; Postolache, O. Multi-AGV scheduling for conflict-free path planning in automated container terminals. *Comput. Ind. Eng.* **2020**, *142*, 106371. [[CrossRef](#)]
4. Masłowski, A. Training in Military Robotics and EOD Unmanned Systems. 2014. Available online: https://www.eodcoe.org/files/en/events/nato-eod-demonstrations-trials-2014/3-nato_eod_trencin-09_2014-maslowski-opt.pdf (accessed on 6 August 2020).
5. Vassev, E.; Hinchey, M. *Autonomy Requirements Engineering for Space Missions*; Springer: Berlin/Heidelberg, Germany, 2014.
6. Gao, W.; Wang, W.; Zhu, H.; Zhao, S.; Huang, G.; Du, Z. Irradiation test and hardness design for mobile rescue robot in nuclear environment. *Ind. Robot. Int. J. Robot. Res. Appl.* **2019**, *46*, 851–862. [[CrossRef](#)]
7. Mir, I.; Akhtar, S.; Eisa, S.; Maqsood, A. Guidance and control of standoff air-to-surface carrier vehicle. *Aeronaut. J.* **2019**, *123*, 283–309. [[CrossRef](#)]
8. Mir, I.; Taha, H.; Eisa, S.A.; Maqsood, A. A controllability perspective of dynamic soaring. *Nonlinear Dyn.* **2018**, *94*, 2347–2362. [[CrossRef](#)]
9. Mir, I.; Eisa, S.A.; Maqsood, A. Review of dynamic soaring: Technical aspects, nonlinear modeling perspectives and future directions. *Nonlinear Dyn.* **2018**, *94*, 3117–3144. [[CrossRef](#)]
10. Mir, I.; Maqsood, A.; Eisa, S.A.; Taha, H.; Akhtar, S. Optimal morphing-augmented dynamic soaring maneuvers for unmanned air vehicle capable of span and sweep morphologies. *Aerosp. Sci. Technol.* **2018**, *79*, 17–36. [[CrossRef](#)]
11. Mir, I.; Eisa, S.A.; Taha, H.E.; Maqsood, A.; Akhtar, S.; Islam, T.U. A stability perspective of bio-inspired UAVs performing dynamic soaring optimally. *Bioinspir. Biomim.* **2021**. [[CrossRef](#)]
12. Fink, J.; Bauwens, V.; Kaplan, F.; Dillenbourg, P. Living with a vacuum cleaning robot. *Int. J. Soc. Robot.* **2013**, *5*, 389–408. [[CrossRef](#)]
13. Häne, C.; Heng, L.; Lee, G.H.; Fraundorfer, F.; Furgale, P.; Sattler, T.; Pollefeys, M. 3D visual perception for self-driving cars using a multi-camera system: Calibration, mapping, localization, and obstacle detection. *Image Vis. Comput.* **2017**, *68*, 14–27. [[CrossRef](#)]
14. Zhou, C.; Huang, B.; Fränti, P. A survey of motion planning algorithms for intelligent robotics. *arXiv* **2021**, arXiv:2102.02376.
15. Contreras-Cruz, M.A.; Ayala-Ramirez, V.; Hernandez-Belmonte, U.H. Mobile robot path planning using artificial bee colony and evolutionary programming. *Appl. Soft Comput.* **2015**, *30*, 319–328. [[CrossRef](#)]
16. Littlefield, Z.; Bekris, K.E. Efficient and asymptotically optimal kinodynamic motion planning via dominance-informed regions. In Proceedings of the 2018 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), Madrid, Spain, 1–5 October 2018; pp. 1–9.
17. Ganeshmurthy, M.; Suresh, G. Path planning algorithm for autonomous mobile robot in dynamic environment. In Proceedings of the 2015 3rd International Conference on Signal Processing, Communication and Networking (ICSCN), Chennai, India, 26–28 March 2015; pp. 1–6.
18. Choset, H.M.; Hutchinson, S.; Lynch, K.M.; Kantor, G.; Burgard, W.; Kavraki, L.E.; Thrun, S.; Arkin, R.C. *Principles of Robot Motion: Theory, Algorithms, and Implementation*; MIT Press: Cambridge, MA, USA, 2005.
19. LaValle, S.M. *Planning Algorithms*; Cambridge University Press: Cambridge, UK, 2006.
20. Aguilar, W.G.; Sandoval, S.; Limaico, A.; Villegas-Pico, M.; Asimbaya, I. Path Planning Based Navigation Using LIDAR for an Ackerman Unmanned Ground Vehicle. In *International Conference on Intelligent Robotics and Applications*; Springer: Berlin/Heidelberg, Germany, 2019; pp. 399–410.
21. Le, A.V.; Nhan, N.H.K.; Mohan, R.E. Evolutionary algorithm-based complete coverage path planning for tetriamond tiling robots. *Sensors* **2020**, *20*, 445. [[CrossRef](#)]
22. Thoma, J.; Paudel, D.P.; Chhatkuli, A.; Probst, T.; Gool, L.V. Mapping, localization and path planning for image-based navigation using visual features and map. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, Long Beach, CA, USA, 15–20 June 2019; pp. 7383–7391.
23. Krell, E.; Sheta, A.; Balasubramanian, A.P.R.; King, S.A. Collision-free autonomous robot navigation in unknown environments utilizing pso for path planning. *J. Artif. Intell. Soft Comput. Res.* **2019**, *9*, 267–282. [[CrossRef](#)]
24. Vis, I.F. Survey of research in the design and control of automated guided vehicle systems. *Eur. J. Oper. Res.* **2006**, *170*, 677–709. [[CrossRef](#)]
25. Sanchez-Lopez, J.L.; Wang, M.; Olivares-Mendez, M.A.; Molina, M.; Voos, H. A real-time 3d path planning solution for collision-free navigation of multirotor aerial robots in dynamic environments. *J. Intell. Robot. Syst.* **2019**, *93*, 33–53. [[CrossRef](#)]
26. Yi, J.H.; Lu, M.; Zhao, X.J. Quantum inspired monarch butterfly optimisation for UCAV path planning navigation problem. *Int. J. Bio-Inspir. Comput.* **2020**, *15*, 75–89. [[CrossRef](#)]
27. Majeed, A.; Lee, S. A new coverage flight path planning algorithm based on footprint sweep fitting for unmanned aerial vehicle navigation in urban environments. *Appl. Sci.* **2019**, *9*, 1470. [[CrossRef](#)]
28. Nicholson, J.; Healey, A. The present state of autonomous underwater vehicle (AUV) applications and technologies. *Mar. Technol. Soc. J.* **2008**, *42*, 44–51. [[CrossRef](#)]

29. Sahoo, A.; Dwivedy, S.K.; Robi, P. Advancements in the field of autonomous underwater vehicle. *Ocean Eng.* **2019**, *181*, 145–160. [[CrossRef](#)]
30. Tzafestas, S.G. Mobile robot path, motion, and task planning. In *Introduction to Mobile Robot Control*; Elsevier: Amsterdam, The Netherlands, 2014; pp. 429–478.
31. Hall, J.K. GEBCO Centennial Special Issue—Charting the secret world of the ocean floor: The GEBCO project 1903–2003. *Mar. Geophys. Res.* **2006**, *27*, 1–5. [[CrossRef](#)]
32. Takács, B.; Dóczy, R.; Sütő, B.; Kalló, J.; Várkonyi, T.A.; Haidegger, T.; Kozlovsky, M. Extending AUV response robot capabilities to solve standardized test methods. *Acta Polytech. Hung.* **2016**, *13*, 157–170.
33. Li, J.H.; Kang, H.; Park, G.H.; Suh, J.H. Real time path planning of underwater robots in unknown environment. In Proceedings of the 2017 International Conference on Control, Artificial Intelligence, Robotics & Optimization (ICCAIRO), Prague, Czech Republic, 20–22 May 2017; pp. 312–318.
34. Wei, M.; Isler, V. Energy-efficient Path Planning for Ground Robots by and Combining Air and Ground Measurements. In Proceedings of the Conference on Robot Learning, Osaka, Japan, 16–18 November 2020; pp. 766–775.
35. Delmerico, J.; Mueggler, E.; Nitsch, J.; Scaramuzza, D. Active autonomous aerial exploration for ground robot path planning. *IEEE Robot. Autom. Lett.* **2017**, *2*, 664–671. [[CrossRef](#)]
36. Marin-Plaza, P.; Hussein, A.; Martin, D.; Escalera, A.d.l. Global and local path planning study in a ROS-based research platform for autonomous vehicles. *J. Adv. Transp.* **2018**, *2018*, 6392697. [[CrossRef](#)]
37. Sombolstan, S.; Rasooli, A.; Khodaygan, S. Optimal path-planning for mobile robots to find a hidden target in an unknown environment based on machine learning. *J. Ambient Intell. Humaniz. Comput.* **2019**, *10*, 1841–1850. [[CrossRef](#)]
38. Tuncer, A.; Yildirim, M. Design and implementation of a genetic algorithm IP core on an FPGA for path planning of mobile robots. *Turk. J. Electr. Eng. Comput. Sci.* **2016**, *24*, 5055–5067. [[CrossRef](#)]
39. Chaari, I.; Koubaa, A.; Bennaceur, H.; Ammar, A.; Alajlan, M.; Youssef, H. Design and performance analysis of global path planning techniques for autonomous mobile robots in grid environments. *Int. J. Adv. Robot. Syst.* **2017**, *14*, 1729881416663663. [[CrossRef](#)]
40. Do, C.H.; Lin, H.Y. Differential evolution for optimizing motion planning of mobile robot. In Proceedings of the 2017 IEEE/SICE International Symposium on System Integration (SII), Taipei, Taiwan, 11–14 December 2017; pp. 399–404.
41. Li, Y.; Cui, R.; Li, Z.; Xu, D. Neural network approximation based near-optimal motion planning with kinodynamic constraints using RRT. *IEEE Trans. Ind. Electron.* **2018**, *65*, 8718–8729. [[CrossRef](#)]
42. Kuntz, N.R.; Oh, P.Y. Development of autonomous cargo transport for an unmanned aerial vehicle using visual servoing. In Proceedings of the Dynamic Systems and Control Conference, 20–22 October 2008; pp. 731–738.
43. O’Young, S.; Hubbard, P. RAVEN: A maritime surveillance project using small UAV. In Proceedings of the 2007 IEEE Conference on Emerging Technologies and Factory Automation (EFTA 2007), Patras, Greece, 25–28 September 2007; pp. 904–907.
44. Primates, S.; Guglieri, G.; Rizzo, A. A risk-aware path planning strategy for uavs in urban environments. *J. Intell. Robot. Syst.* **2019**, *95*, 629–643. [[CrossRef](#)]
45. Rochin, F.R.; Yamazoe, H.; Lee, J.H. Autonomous Coverage Path Planning and Navigation Control System for Search Operations using a UAV. In Proceedings of the 2019 16th International Conference on Ubiquitous Robots (UR), Jeju, Korea, 24–27 June 2019; pp. 194–199.
46. Naazare, M.; Ramos, D.; Wildt, J.; Schulz, D. Application of Graph-based Path Planning for UAVs to Avoid Restricted Areas. In Proceedings of the 2019 IEEE International Symposium on Safety, Security, and Rescue Robotics (SSRR), Würzburg, Germany, 2–4 September 2019; pp. 139–144.
47. Qin, H.; Meng, Z.; Meng, W.; Chen, X.; Sun, H.; Lin, F.; Ang, M.H. Autonomous exploration and mapping system using heterogeneous UAVs and UGVs in GPS-denied environments. *IEEE Trans. Veh. Technol.* **2019**, *68*, 1339–1350. [[CrossRef](#)]
48. Kinsey, J.C.; Eustice, R.M.; Whitcomb, L.L. A survey of underwater vehicle navigation: Recent advances and new challenges. In Proceedings of the IFAC Conference of Manoeuvring and Control of Marine Craft, Lisbon, Portugal, 20–22 September 2006; Volume 88, pp. 1–12.
49. Bertozzi, M.; Broggi, A.; Fascioli, A. Vision-based intelligent vehicles: State of the art and perspectives. *Robot. Auton. Syst.* **2000**, *32*, 1–16. [[CrossRef](#)]
50. Franke, U.; Gavrila, D.; Gern, A.; Görzig, S.; Janssen, R.; Paetzold, F.; Wöhler, C. From door to door—Principles and applications of computer vision for driver assistant systems. In *Intelligent Vehicle Technologies*; Elsevier: Amsterdam, The Netherlands, 2001; pp. 131–188.
51. Dickmanns, E.D.; Behringer, R.; Dickmanns, D.; Hildebrandt, T.; Maurer, M.; Thomaneck, F.; Schiehlen, J. The seeing passenger car ‘VaMoRs-P’. In Proceedings of the Intelligent Vehicles’ 94 Symposium, Paris, France, 24–26 October 1994; pp. 68–73.
52. Nagel, H.H.; Enkelmann, W.; Struck, G. FhG-Co-Driver: From map-guided automatic driving by machine vision to a cooperative driver support. *Math. Comput. Model.* **1995**, *22*, 185–212. [[CrossRef](#)]
53. Thorpe, C.; Hebert, M.H.; Kanade, T.; Shafer, S.A. Vision and navigation for the Carnegie-Mellon Navlab. *IEEE Trans. Pattern Anal. Mach. Intell.* **1988**, *10*, 362–373. [[CrossRef](#)]
54. Wood, G.R. The bisection method in higher dimensions. *Math. Program.* **1992**, *55*, 319–337. [[CrossRef](#)]
55. Verbeke, J.; Cools, R. The Newton-Raphson method. *Int. J. Math. Educ. Sci. Technol.* **1995**, *26*, 177–193. [[CrossRef](#)]
56. Hull, T.; Enright, W.H.; Jackson, K. Runge-Kutta Research at Toronto. *Appl. Numer. Math.* **1996**, *22*, 225–236. [[CrossRef](#)]

57. Noor, M.A.; Noor, K.I.; Al-Said, E.; Waseem, M. Some new iterative methods for nonlinear equations. *Math. Probl. Eng.* **2010**, *2010*, 198943. [[CrossRef](#)]
58. Gul, F.; Rahiman, W.; Nazli Alhady, S.S. A comprehensive study for robot navigation techniques. *Cogent Eng.* **2019**, *6*, 1632046. [[CrossRef](#)]
59. Dai, X.; Long, S.; Zhang, Z.; Gong, D. Mobile robot path planning based on ant colony algorithm with A* heuristic method. *Front. Neurobot.* **2019**, *13*, 15. [[CrossRef](#)]
60. Xu, Y.; Fan, P.; Yuan, L. A simple and efficient artificial bee colony algorithm. *Math. Probl. Eng.* **2013**, *2013*, 526315. [[CrossRef](#)]
61. Dewang, H.S.; Mohanty, P.K.; Kundu, S. A robust path planning for mobile robot using smart particle swarm optimization. *Procedia Comput. Sci.* **2018**, *133*, 290–297. [[CrossRef](#)]
62. Lamini, C.; Benhlima, S.; Elbekri, A. Genetic algorithm based approach for autonomous mobile robot path planning. *Procedia Comput. Sci.* **2018**, *127*, 180–189. [[CrossRef](#)]
63. Mirjalili, S.; Lewis, A. The whale optimization algorithm. *Adv. Eng. Softw.* **2016**, *95*, 51–67. [[CrossRef](#)]
64. Mirjalili, S.; Mirjalili, S.M.; Lewis, A. Grey wolf optimizer. *Adv. Eng. Softw.* **2014**, *69*, 46–61. [[CrossRef](#)]
65. Meraihi, Y.; Ramdane-Cherif, A.; Acheli, D.; Mahseur, M. Dragonfly algorithm: A comprehensive review and applications. *Neural Comput. Appl.* **2020**, *32*, 16625–16646. [[CrossRef](#)]
66. Abualigah, L.; Shehab, M.; Alshinwan, M.; Alabool, H. Salp swarm algorithm: A comprehensive survey. *Neural Comput. Appl.* **2020**, *32*, 11195–11215. [[CrossRef](#)]
67. Saremi, S.; Mirjalili, S.; Lewis, A. Grasshopper optimisation algorithm: Theory and application. *Adv. Eng. Softw.* **2017**, *105*, 30–47. [[CrossRef](#)]
68. Mirjalili, S. The ant lion optimizer. *Adv. Eng. Softw.* **2015**, *83*, 80–98. [[CrossRef](#)]
69. Mirjalili, S. Moth-flame optimization algorithm: A novel nature-inspired heuristic paradigm. *Knowl.-Based Syst.* **2015**, *89*, 228–249. [[CrossRef](#)]
70. Ma, G.; Zhang, Y.; Nee, A. A simulated annealing-based optimization algorithm for process planning. *Int. J. Prod. Res.* **2000**, *38*, 2671–2687. [[CrossRef](#)]
71. Brammya, G.; Praveena, S.; Ninu Preetha, N.; Ramya, R.; Rajakumar, B.; Binu, D. Deer hunting optimization algorithm: A new nature-inspired meta-heuristic paradigm. *Comput. J.* **2019**. [[CrossRef](#)]
72. Gao, X.Z.; Govindasamy, V.; Xu, H.; Wang, X.; Zenger, K. Harmony search method: Theory and applications. *Comput. Intell. Neurosci.* **2015**, *2015*, 258491. [[CrossRef](#)]
73. Jain, M.; Maurya, S.; Rani, A.; Singh, V. Owl search algorithm: A novel nature-inspired heuristic paradigm for global optimization. *J. Intell. Fuzzy Syst.* **2018**, *34*, 1573–1582. [[CrossRef](#)]
74. Gul, F.; Rahiman, W.; Alhady, S.N.; Ali, A.; Mir, I.; Jalil, A. Meta-heuristic approach for solving multi-objective path planning for autonomous guided robot using PSO—GWO optimization algorithm with evolutionary programming. *J. Ambient. Intell. Humaniz. Comput.* **2021**, *12*, 7873–7890. [[CrossRef](#)]
75. Yiqing, L.; Xigang, Y.; Yongjian, L. An improved PSO algorithm for solving non-convex NLP/MINLP problems with equality constraints. *Comput. Chem. Eng.* **2007**, *31*, 153–162. [[CrossRef](#)]
76. Huang, W.H.; Fajen, B.R.; Fink, J.R.; Warren, W.H. Visual navigation and obstacle avoidance using a steering potential function. *Robot. Auton. Syst.* **2006**, *54*, 288–299. [[CrossRef](#)]
77. Gul, F.; Rahiman, W. An Integrated approach for Path Planning for Mobile Robot Using Bi-RRT. In *IOP Conference Series: Materials Science and Engineering*; IOP Publishing: Bristol, UK, 2019; Volume 697, p. 012022.
78. Montiel, O.; Orozco-Rosas, U.; Sepúlveda, R. Path planning for mobile robots using Bacterial Potential Field for avoiding static and dynamic obstacles. *Expert Syst. Appl.* **2015**, *42*, 5177–5191. [[CrossRef](#)]
79. Rao, A.V. A survey of numerical methods for optimal control. *Adv. Astronaut. Sci.* **2009**, *135*, 497–528.
80. Bellman, R. Dynamic Programming. In *New Jersey Google Scholar*; Princeton University Press: Princeton, NJ, USA, 1957.
81. Bellman, R. Dynamic programming treatment of the travelling salesman problem. *J. ACM (JACM)* **1962**, *9*, 61–63. [[CrossRef](#)]
82. Gerdts, M. Direct shooting method for the numerical solution of higher-index DAE optimal control problems. *J. Optim. Theory Appl.* **2003**, *117*, 267. [[CrossRef](#)]
83. Cannataro, B.S.; Rao, A.V.; Davis, T.A. State-defect constraint pairing graph coarsening method for Karush–Kuhn–Tucker matrices arising in orthogonal collocation methods for optimal control. *Comput. Optim. Appl.* **2016**, *64*, 793–819. [[CrossRef](#)]
84. Huntington, G.T.; Rao, A.V. Comparison of global and local collocation methods for optimal control. *J. Guid. Control. Dyn.* **2008**, *31*, 432. [[CrossRef](#)]
85. Schwartz, A.L. Theory and Implementation of Numerical Methods Based on Runge-Kutta Integration for Solving Optimal Control Problems. Ph.D. Thesis, University of California, Berkeley, CA, USA, 1996.
86. Reddien, G. Collocation at Gauss points as a discretization in optimal control. *SIAM J. Control Optim.* **1979**, *17*, 298–306. [[CrossRef](#)]
87. Abualigah, L.; Yousri, D.; Abd Elaziz, M.; Ewees, A.A.; Al-qaness, M.A.; Gandomi, A.H. Aquila Optimizer: A novel meta-heuristic optimization Algorithm. *Comput. Ind. Eng.* **2021**, *157*, 107250. [[CrossRef](#)]
88. Rao, A.V.; Benson, D.A.; Darby, C.; Patterson, M.A.; Franconin, C.; Sanders, I.; Huntington, G.T. Algorithm 902: Gpops, a matlab software for solving multiple-phase optimal control problems using the gauss pseudospectral method. *ACM Trans. Math. Softw. (TOMS)* **2010**, *37*, 22. [[CrossRef](#)]

89. Darby, C.L.; Hager, W.W.; Rao, A.V. An hp-adaptive pseudospectral method for solving optimal control problems. *Optim. Control Appl. Methods* **2011**, *32*, 476–502. [[CrossRef](#)]
90. Sachs, G.; da Costa, O. Optimization of dynamic soaring at ridges. In Proceedings of the AIAA Atmospheric Flight Mechanics Conference and Exhibit, Austin, TX, USA, 11–14 August 2003; pp. 11–14.
91. Sachs, G. Minimum shear wind strength required for dynamic soaring of albatrosses. *IBIS* **2005**, *147*, 1–10. [[CrossRef](#)]
92. Sachs, G.; Mayrhofer, M. Shear wind strength required for dynamic soaring at ridges. *Tech. Soar.* **2001**, *25*, 209–215.
93. Well, K. Graphical environment for simulation and optimization. In *Department of Optimization, Guidance, and Control*; Springer: Stuttgart, Germany, 2002.
94. Wiegand, A. ASTOS User Manual. *Unterkirnach Ger. Astos Solut. GmbH* **2010**, *17*, 34–52.
95. Sachs, G.; Knoll, A.; Lesch, K. Optimal utilization of wind energy for dynamic soaring. *Tech. Soar.* **1991**, *15*, 48–55.
96. Zhao, Y.J. Optimal patterns of glider dynamic soaring. *Optim. Control Appl. Methods* **2004**, *25*, 67–89. [[CrossRef](#)]
97. Zhao, Y.J.; Qi, Y.C. Minimum fuel powered dynamic soaring of unmanned aerial vehicles utilizing wind gradients. *Optim. Control Appl. Methods* **2004**, *25*, 211–233. [[CrossRef](#)]
98. Gill, P.E.; Murray, W.; Saunders, M.A.; Wright, M.H. *User's Guide for NPSOL (version 4.0): A Fortran Package for Nonlinear Programming*; Technical Report; Stanford Univ Ca Systems Optimization LAB: Stanford, CA, USA, 1986.
99. Akhtar, N. Control System Development for Autonomous Soaring. 2010. Available online: www.dspace.lib.cranfield.ac.uk/handle/1826/6899 (accessed on 6 August 2021).
100. Akhtar, N.; Whidborne, J.; Cooke, A. Real-time optimal techniques for unmanned air vehicles fuel saving. *Proc. Inst. Mech. Eng. Part G: J. Aerosp. Eng.* **2012**, *226*, 1315–1328. [[CrossRef](#)]
101. Akhtar, N.; Whidborne, J.F.; Cooke, A.K. Wind shear energy extraction using dynamic soaring techniques. *Am. Inst. Aeronaut. Astronaut. AIAA* **2009**, 734. [[CrossRef](#)]
102. Abualigah, L.; Diabat, A.; Mirjalili, S.; Abd Elaziz, M.; Gandomi, A.H. The arithmetic optimization algorithm. *Comput. Methods Appl. Mech. Eng.* **2021**, *376*, 113609. [[CrossRef](#)]
103. Mir, I.; Maqsood, A.; Akhtar, S. Biologically Inspired Dynamic Soaring Maneuvers for an Unmanned Air Vehicle Capable of Sweep Morphing. *Int. J. Aeronaut. Space Sci.* **2018**, *19*, 1006–1016. [[CrossRef](#)]
104. Wu, Y.; Gou, J.; Hu, X.; Huang, Y. A new consensus theory-based method for formation control and obstacle avoidance of UAVs. *Aerosp. Sci. Technol.* **2020**, 106332. [[CrossRef](#)]
105. Li, X.; Luo, C.; Xu, Y.; Li, P. A Fuzzy PID controller applied in AGV control system. In Proceedings of the 2016 International Conference on Advanced Robotics and Mechatronics (ICARM), Macau, China, 18–20 August 2016; pp. 555–560.
106. Matveev, A.S.; Wang, C.; Savkin, A.V. Real-time navigation of mobile robots in problems of border patrolling and avoiding collisions with moving and deforming obstacles. *Robot. Auton. Syst.* **2012**, *60*, 769–788. [[CrossRef](#)]
107. Li, Y.; Wang, X.N.; Li, S.J.; Zhu, J. LQR based Trajectory Tracking Control for Forked AGV. In *Applied Mechanics and Materials*; Trans Tech Publications Ltd: Baech, Switzerland, 2014; Volume 577, pp. 447–451.
108. Castillo, O.; Aguilar, L.T.; Cárdenas, S. Fuzzy Logic Tracking Control for Unicycle Mobile Robots. *Eng. Lett.* **2006**, *13*, 1–5.
109. Dumitrascu, B.; Filipescu, A.; Minzu, V. Backstepping control of wheeled mobile robots. In Proceedings of the 15th International Conference on System Theory, Control and Computing, Sinaia, Romania, 14–16 October 2011; pp. 1–6.
110. Gul, F.; Alhady, S.S.N.; Rahiman, W. A review of control algorithm for autonomous guided vehicle. *Indones. J. Electr. Eng. Comput. Sci.* **2020**, *20*, 552–562. [[CrossRef](#)]
111. Alsultan, T.; M. Ali, H.; Y. Hamid, Q. A numerical approach for solving problems in robotic arm movement. *Prod. Manuf. Res.* **2018**, *6*, 385–395.
112. Yuan, P.; Su, F.; Shi, Z.; Wang, T.; Chen, D. Autonomous path planning solution for industrial robot manipulator using backpropagation algorithm. *Adv. Mech. Eng.* **2015**, *7*, 1687814015619768. [[CrossRef](#)]
113. Majumdar, A.; Ahmadi, A.A.; Tedrake, R. Control design along trajectories with sums of squares programming. In Proceedings of the 2013 IEEE International Conference on Robotics and Automation, Karlsruhe, Germany, 6–10 May 2013; pp. 4054–4061.
114. Saudi, A.; Sulaiman, J. Numerical technique for robot path planning using four Point-EG iterative method. In Proceedings of the 2010 International Symposium on Information Technology, Kuala Lumpur, Malaysia, 15–17 June 2010; Volume 2, pp. 831–836.
115. Li, J.; Sun, J.; Chen, G. A Multi-Switching Tracking Control Scheme for Autonomous Mobile Robot in Unknown Obstacle Environments. *Electronics* **2020**, *9*, 42. [[CrossRef](#)]
116. Leonard, J.J.; Bennett, A.A.; Smith, C.M.; Jacob, H.; Feder, S. Autonomous Underwater Vehicle Navigation. MIT Marine Robotics Laboratory Technical Memorandum. Citeseer. 1998. Available online: www.cml.mit.edu/~jleonard/pubs/techreport981.pdf (accessed on 6 August 2020)
117. Leonard, J.J.; Bahr, A. Autonomous underwater vehicle navigation. In *Springer Handbook of Ocean Engineering*; Springer: Berlin/Heidelberg, Germany, 2016; pp. 341–358.
118. Bedwell, I. Australian Sonar Transducer Technology. Available online: https://www.academia.edu/download/62864992/Bedwell_Australian_Sonar_Transducer_Technology_120200407-14290-1e51qex.pdf (accessed on 20 November 2013).
119. Miller, P.A.; Farrell, J.A.; Zhao, Y.; Djapic, V. Autonomous underwater vehicle navigation. *IEEE J. Ocean. Eng.* **2010**, *35*, 663–678. [[CrossRef](#)]

120. Bobkov, V.; Kudryashov, A.; Melman, S.; Scherbatyuk, A. Visual navigation and 3D reconstruction of underwater objects with autonomous underwater vehicle. In Proceedings of the 2017 24th Saint Petersburg International Conference on Integrated Navigation Systems (ICINS), St. Petersburg, Russia, 29–31 May 2017; pp. 1–5.
121. Pérez-Alcocer, R.; Torres-Méndez, L.A.; Olguín-Díaz, E.; Maldonado-Ramírez, A.A. Vision-based autonomous underwater vehicle navigation in poor visibility conditions using a model-free robust control. *J. Sens.* **2016**, *2016*, 8594096. [[CrossRef](#)]
122. Ko, N.Y.; Choi, H.T.; Lee, C.M.; Moon, Y.S. Attitude estimation using depth measurement and AHRS data for underwater vehicle navigation. In Proceedings of the OCEANS 2016-Shanghai, Shanghai, China, 10–13 April 2016; pp. 1–4.
123. Alexandri, T.; Diamant, R. A reverse bearings only target motion analysis for autonomous underwater vehicle navigation. *IEEE Trans. Mob. Comput.* **2018**, *18*, 494–506. [[CrossRef](#)]
124. Frese, U.; Büscher, D.; Burgard, W. Novel Directions for Autonomous Underwater Vehicle Navigation in Confined Spaces. In *AI Technology for Underwater Robots*; Springer: Berlin/Heidelberg, Germany, 2020; pp. 157–168.
125. Chen, D.; Neusypin, K.; Selezneva, M. Correction Algorithm for the Navigation System of an Autonomous Unmanned Underwater Vehicle. *Sensors* **2020**, *20*, 2365. [[CrossRef](#)]
126. Gao, X.Z.; Hou, Z.X.; Guo, Z.; Fan, R.F.; Chen, X.Q. Analysis and design of guidance-strategy for dynamic soaring with UAVs. *Control Eng. Pract.* **2014**, *32*, 218–226. [[CrossRef](#)]
127. Benson, D.A.; Huntington, G.T.; Thorvaldsen, T.P.; Rao, A.V. Direct trajectory optimization and costate estimation via an orthogonal collocation method. *J. Guid. Control. Dyn.* **2006**, *29*, 1435–1440. [[CrossRef](#)]
128. Garg, D.; Patterson, M.A.; Francolin, C.; Darby, C.L.; Huntington, G.T.; Hager, W.W.; Rao, A.V. Direct trajectory optimization and costate estimation of finite-horizon and infinite-horizon optimal control problems using a Radau pseudospectral method. *Comput. Optim. Appl.* **2011**, *49*, 335–358. [[CrossRef](#)]
129. Zhang, Z.; Li, J.; Wang, J. Sequential convex programming for nonlinear optimal control problems in UAV path planning. *Aerosp. Sci. Technol.* **2018**, *76*, 280–290. [[CrossRef](#)]
130. Abdelkawy, M.; Lopes, A.M.; Babatin, M.M. Shifted fractional Jacobi collocation method for solving fractional functional differential equations of variable order. *Chaos Solitons Fractals* **2020**, *134*, 109721. [[CrossRef](#)]
131. Zollars, M.D.; Cobb, R.G. Simplex Methods for Optimal Control of Unmanned Aircraft Flight Trajectories. In *Dynamic Systems and Control Conference*; American Society of Mechanical Engineers: New York, NY, USA, 2017; Volume 58295, p. V003T39A001.
132. Masehian, E.; Amin-Naseri, M. A voronoi diagram-visibility graph-potential field compound algorithm for robot path planning. *J. Robot. Syst.* **2004**, *21*, 275–300. [[CrossRef](#)]
133. Majeed, A.; Lee, S. A fast global flight path planning algorithm based on space circumscription and sparse visibility graph for unmanned aerial vehicle. *Electronics* **2018**, *7*, 375. [[CrossRef](#)]
134. Mammarella, M.; Capello, E. A robust MPC-based autopilot for mini UAVs. In Proceedings of the 2018 International Conference on Unmanned Aircraft Systems (ICUAS), Dallas, TX, USA, 12–15 June 2018; pp. 1227–1235.
135. Hemakumara, P.; Sukkariéh, S. Non-parametric UAV system identification with dependent Gaussian processes. In Proceedings of the 2011 IEEE International Conference on Robotics and Automation, Shanghai, China, 9–13 May 2011; pp. 4435–4441.
136. Zou, Y.; Zhang, H.; He, W. Adaptive Coordinated Formation Control of Heterogeneous Vertical Takeoff and Landing UAVs Subject to Parametric Uncertainties. *IEEE Trans. Cybern.* **2020**, 1–12. [[CrossRef](#)]
137. Siddique, N.; Adeli, H. Nature inspired computing: An overview and some future directions. *Cogn. Comput.* **2015**, *7*, 706–714. [[CrossRef](#)]
138. Zhang, Y.; Guan, G.; Pu, X. The robot path planning based on improved artificial fish swarm algorithm. *Math. Probl. Eng.* **2016**, *2016*, 3297585. [[CrossRef](#)]
139. Wang, H.J.; Fu, Y.; Zhao, Z.Q.; Yue, Y.J. An Improved Ant Colony Algorithm of Robot Path Planning for Obstacle Avoidance. *J. Robot.* **2019**, *2019*, 6097591. [[CrossRef](#)]
140. Safari, M.; Mahjoob, M. Bee colony algorithm for real-time optimal path planning of mobile robots. In Proceedings of the 2009 Fifth International Conference on Soft Computing, Computing with Words and Perceptions in System Analysis, Decision and Control, Famagusta, North Cyprus, 2–4 September 2009; pp. 1–4.
141. Dao, T.K.; Pan, T.S.; Pan, J.S. A multi-objective optimal mobile robot path planning based on whale optimization algorithm. In Proceedings of the 2016 IEEE 13th International Conference on Signal Processing (ICSP), Chengdu, China, 6–10 November 2016; pp. 337–342.
142. Tsai, P.W.; Dao, T.K.; others. Robot path planning optimization based on multiobjective grey wolf optimizer. In *International Conference on Genetic and Evolutionary Computing*; Springer: Berlin/Heidelberg, Germany, 2016; pp. 166–173.
143. Guo, J.; Gao, Y.; Cui, G. The path planning for mobile robot based on bat algorithm. *Int. J. Autom. Control* **2015**, *9*, 50–60. [[CrossRef](#)]
144. Yang, X.S. *Nature-Inspired Metaheuristic Algorithms*; Luniver Press: Bristol, UK, 2010.
145. Chaturvedi, D. Soft Computing Techniques and Their Applications. In *Mathematical Models, Methods and Applications*; Springer: Berlin/Heidelberg, Germany, 2015; pp. 31–40.
146. Wang, P.; Gao, S.; Li, L.; Sun, B.; Cheng, S. Obstacle avoidance path planning design for autonomous driving vehicles based on an improved artificial potential field algorithm. *Energies* **2019**, *12*, 2342. [[CrossRef](#)]
147. Surmann, H.; Kanstein, A.; Goser, K. Self-Organizing and Genetic Algorithms for an Automatic Design of Fuzzy Control and Decision Systems. In *Proceedings of the EUFIT'93*; Citeseer: Princeton, NJ, USA, 1993.

148. Payne, D.; Stern, J. Wavelength-switched passively coupled single-mode optical network. In Proceedings of the IOOC-ECOC, Venezia, Italy, 1–4 October 1985; Volume 85, p. 585.
149. Karaboga, D.; Akay, B. A comparative study of artificial bee colony algorithm. *Appl. Math. Comput.* **2009**, *214*, 108–132. [[CrossRef](#)]
150. Baykasoğlu, A.; Özbakır, L.; Tapkan, P. Artificial Bee Colony Algorithm and Its Application to Generalized Assignment Problem Swarm Intelligence Focus on Ant and Particle Swarm Optimization. 17 December 2007. Available online: www.10.5772/5101 (accessed on 6 August 2021).
151. Kamil, R.T.; Mohamed, M.J.; Oleiwi, B.K. Path Planning of Mobile Robot Using Improved Artificial Bee Colony Algorithm. *Eng. Technol. J.* **2020**, *38*, 1384–1395. [[CrossRef](#)]
152. Ismail, A.; Sheta, A.; Al-Weshah, M. A mobile robot path planning using genetic algorithm in static environment. *J. Comput. Sci.* **2008**, *4*, 341–344.
153. Mitchell, M. *An Introduction to Genetic Algorithms*; MIT Press: Cambridge, MA, USA, 1998.
154. Xin, D.; Hua-hua, C.; Wei-kang, G. Neural network and genetic algorithm based global path planning in a static environment. *J. Zhejiang Univ.-Sci. A* **2005**, *6*, 549–554. [[CrossRef](#)]
155. Li, J.; Deng, G.; Luo, C.; Lin, Q.; Yan, Q.; Ming, Z. A hybrid path planning method in unmanned air/ground vehicle (UAV/UGV) cooperative systems. *IEEE Trans. Veh. Technol.* **2016**, *65*, 9585–9596. [[CrossRef](#)]
156. Lee, J.; Kang, B.Y.; Kim, D.W. Fast genetic algorithm for robot path planning. *Electron. Lett.* **2013**, *49*, 1449–1451. [[CrossRef](#)]
157. Tian, L.; Collins, C. An effective robot trajectory planning method using a genetic algorithm. *Mechatronics* **2004**, *14*, 455–470. [[CrossRef](#)]
158. Han, W.G.; Baek, S.M.; Kuc, T.Y. Genetic algorithm based path planning and dynamic obstacle avoidance of mobile robots. In Proceedings of the 1997 IEEE International Conference on Systems, Man, and Cybernetics. Computational Cybernetics and Simulation, Orlando, FL, USA, 12–15 October 1997; Volume 3, pp. 2747–2751.
159. Châari, I.; Koubaa, A.; Bennaceur, H.; Trigui, S.; Al-Shalfan, K. SmartPATH: A hybrid ACO-GA algorithm for robot path planning. In Proceedings of the 2012 IEEE congress on evolutionary computation, Brisbane, QLD, Australia, 10–15 June 2012; pp. 1–8.
160. Geisler, T.; Manikas, T.W. Autonomous robot navigation system using a novel value encoded genetic algorithm. In Proceedings of the 2002 45th Midwest Symposium on Circuits and Systems, 2002, MWSCAS-2002, Tulsa, OK, USA, 4–7 August 2002; Volume 3, pp. III–III
161. Liu, K.; Zhang, M. Path planning based on simulated annealing ant colony algorithm. In Proceedings of the 2016 9th International Symposium on Computational Intelligence and Design (ISCID), Hangzhou, China, 10–11 December 2016; Volume 2, pp. 461–466.
162. Zhang, S.; Zhou, Y.; Li, Z.; Pan, W. Grey wolf optimizer for unmanned combat aerial vehicle path planning. *Adv. Eng. Softw.* **2016**, *99*, 121–136. [[CrossRef](#)]
163. Hussien, A.G.; Amin, M.; Abd El Aziz, M. A comprehensive review of moth-flame optimisation: Variants, hybrids, and applications. *J. Exp. Theor. Artif. Intell.* **2020**, *32*, 705–725. [[CrossRef](#)]
164. Watkins, W.A.; Schevill, W.E. Aerial observation of feeding behavior in four baleen whales: *Eubalaena glacialis*, *Balaenoptera borealis*, *Megaptera novaeangliae*, and *Balaenoptera physalus*. *J. Mammal.* **1979**, *60*, 155–163. [[CrossRef](#)]
165. Goldbogen, J.A.; Friedlaender, A.S.; Calambokidis, J.; Mckenna, M.F.; Simon, M.; Nowacek, D.P. Integrative approaches to the study of baleen whale diving behavior, feeding performance, and foraging ecology. *BioScience* **2013**, *63*, 90–100. [[CrossRef](#)]
166. Silva Arantes, J.d.; Silva Arantes, M.d.; Motta Toledo, C.F.; Júnior, O.T.; Williams, B.C. Heuristic and genetic algorithm approaches for UAV path planning under critical situation. *Int. J. Artif. Intell. Tools* **2017**, *26*, 1760008. [[CrossRef](#)]
167. Qu, C.; Gai, W.; Zhang, J.; Zhong, M. A novel hybrid grey wolf optimizer algorithm for unmanned aerial vehicle (UAV) path planning. *Knowl.-Based Syst.* **2020**, *194*, 105530. [[CrossRef](#)]
168. Dewangan, R.K.; Shukla, A.; Godfrey, W.W. Three dimensional path planning using Grey wolf optimizer for UAVs. *Appl. Intell.* **2019**, *49*, 2201–2217. [[CrossRef](#)]
169. Soundarya, M.; Anusha, D.K.; Rohith, P.; Panneerselvam, K.; Srinivasan, S. Optimal path planning of UAV using grey wolf optimiser. *Int. J. Comput. Syst. Eng.* **2019**, *5*, 129–136.
170. Shamsfakhr, F.; Bigham, B.S. A neural network approach to navigation of a mobile robot and obstacle avoidance in dynamic and unknown environments. *Turk. J. Electr. Eng. Comput. Sci.* **2017**, *25*, 1629–1642. [[CrossRef](#)]
171. Ran, L.; Zhang, Y.; Zhang, Q.; Yang, T. Convolutional neural network-based robot navigation using uncalibrated spherical images. *Sensors* **2017**, *17*, 1341. [[CrossRef](#)] [[PubMed](#)]
172. Singh, N.H.; Thongam, K. Neural network-based approaches for mobile robot navigation in static and moving obstacles environments. *Intell. Serv. Robot.* **2019**, *12*, 55–67. [[CrossRef](#)]
173. Almasri, M.M.; Elleithy, K.M.; Alajlan, A.M. Development of efficient obstacle avoidance and line following mobile robot with the integration of fuzzy logic system in static and dynamic environments. In Proceedings of the 2016 IEEE Long Island Systems, Applications and Technology Conference (LISAT), Farmingdale, NY, USA, 29 April 2016; pp. 1–6.
174. Ibrahim, M.I.; Sariff, N.; Johari, J.; Buniyamin, N. Mobile robot obstacle avoidance in various type of static environments using fuzzy logic approach. In Proceedings of the 2014 2nd International Conference on Electrical, Electronics and System Engineering (ICEESE), Kuala Lumpur, Malaysia, 9–10 December 2014; pp. 83–88.
175. Dirik, M.; Castillo, O.; Kocamaz, A.F. Visual-servoing based global path planning using interval type-2 fuzzy logic control. *Axioms* **2019**, *8*, 58. [[CrossRef](#)]

176. Yan, Y.; Li, Y. Mobile robot autonomous path planning based on fuzzy logic and filter smoothing in dynamic environment. In Proceedings of the 2016 12th World congress on intelligent control and automation (WCICA), Guilin, China, 12–15 June 2016; pp. 1479–1484.
177. Patle, B.; Parhi, D.; Jagadeesh, A.; Kashyap, S.K. Matrix-Binary Codes based Genetic Algorithm for path planning of mobile robot. *Comput. Electr. Eng.* **2018**, *67*, 708–728. [[CrossRef](#)]
178. Rath, A.K.; Parhi, D.R.; Das, H.C.; Kumar, P.B.; Muni, M.K.; Salony, K. Path optimization for navigation of a humanoid robot using hybridized fuzzy-genetic algorithm. *Int. J. Intell. Unmanned Syst.* **2019**, *7*. [[CrossRef](#)]
179. Bakdi, A.; Hentout, A.; Boutami, H.; Maoudj, A.; Hachour, O.; Bouzouia, B. Optimal path planning and execution for mobile robots using genetic algorithm and adaptive fuzzy-logic control. *Robot. Auton. Syst.* **2017**, *89*, 95–109. [[CrossRef](#)]
180. Nazarahari, M.; Khanmirza, E.; Doostie, S. Multi-objective multi-robot path planning in continuous environment using an enhanced genetic algorithm. *Expert Syst. Appl.* **2019**, *115*, 106–120. [[CrossRef](#)]
181. Darwish, A.H.; Joukhadar, A.; Kashkash, M. Using the Bees Algorithm for wheeled mobile robot path planning in an indoor dynamic environment. *Cogent Eng.* **2018**, *5*, 1426539. [[CrossRef](#)]
182. Liang, J.H.; Lee, C.H. Efficient collision-free path-planning of multiple mobile robots system using efficient artificial bee colony algorithm. *Adv. Eng. Softw.* **2015**, *79*, 47–56. [[CrossRef](#)]
183. Wu, H.S.; Zhang, F.M. Wolf pack algorithm for unconstrained global optimization. *Math. Probl. Eng.* **2014**, *2014*. [[CrossRef](#)]
184. Liu, C.; Yan, X.; Liu, C.; Wu, H. The wolf colony algorithm and its application. *Chin. J. Electron.* **2011**, *20*, 212–216.
185. Mittal, N.; Singh, U.; Sohi, B.S. Modified grey wolf optimizer for global engineering optimization. *Appl. Comput. Intell. Soft Comput.* **2016**, *2016*, 7950348. [[CrossRef](#)]
186. Li, L.; Sun, L.; Guo, J.; Qi, J.; Xu, B.; Li, S. Modified discrete grey wolf optimizer algorithm for multilevel image thresholding. *Comput. Intell. Neurosci.* **2017**, *2017*, 3295769. [[CrossRef](#)]
187. Mirjalili, S.; Saremi, S.; Mirjalili, S.M.; Coelho, L.d.S. Multi-objective grey wolf optimizer: A novel algorithm for multi-criterion optimization. *Expert Syst. Appl.* **2016**, *47*, 106–119. [[CrossRef](#)]
188. Singh, N.; Singh, S. Hybrid algorithm of particle swarm optimization and grey wolf optimizer for improving convergence performance. *J. Appl. Math.* **2017**, *2017*, 2030489. [[CrossRef](#)]
189. Muro, C.; Escobedo, R.; Spector, L.; Coppinger, R. Wolf-pack (*Canis lupus*) hunting strategies emerge from simple rules in computational simulations. *Behav. Process.* **2011**, *88*, 192–197. [[CrossRef](#)]
190. Rodríguez, L.; Castillo, O.; Soria, J.; Melin, P.; Valdez, F.; Gonzalez, C.I.; Martinez, G.E.; Soto, J. A fuzzy hierarchical operator in the grey wolf optimizer algorithm. *Appl. Soft Comput.* **2017**, *57*, 315–328. [[CrossRef](#)]
191. Jalali, S.M.J.; Hedjam, R.; Khosravi, A.; Heidari, A.A.; Mirjalili, S.; Nahavandi, S. Autonomous robot navigation using moth-flame-based neuroevolution. In *Evolutionary Machine Learning Techniques*; Springer: Berlin/Heidelberg, Germany, 2020; pp. 67–83.
192. Jalali, S.M.J.; Khosravi, A.; Kebria, P.M.; Hedjam, R.; Nahavandi, S. Autonomous robot navigation system using the evolutionary multi-verse optimizer algorithm. In Proceedings of the 2019 IEEE International Conference on Systems, Man and Cybernetics (SMC), Bari, Italy, 6–9 October 2019; pp. 1221–1226.
193. Gharehchopogh, F.S.; Gholizadeh, H. A comprehensive survey: Whale Optimization Algorithm and its applications. *Swarm Evol. Comput.* **2019**, *48*, 1–24. [[CrossRef](#)]
194. Chhillar, A.; Choudhary, A. Mobile Robot Path Planning Based Upon Updated Whale Optimization Algorithm. In Proceedings of the 2020 10th International Conference on Cloud Computing, Data Science & Engineering (Confluence), Noida, India, 29–31 January 2020; pp. 684–691.
195. Zhenxing, Z.; Rennong, Y.; Huanyu, L.; Yuhuan, F.; Zhenyu, H.; Ying, Z. Antlion optimizer algorithm based on chaos search and its application. *J. Syst. Eng. Electron.* **2019**, *30*, 352–365.
196. Rout, A.; Mahanta, G.B.; Bbvl, D.; Biswal, B.B. Kinematic and Dynamic Optimal Trajectory Planning of Industrial Robot Using Improved Multi-objective Ant Lion Optimizer. *J. Inst. Eng. (India) Ser.* **2020**, *101*, 559–569. [[CrossRef](#)]
197. Lucas, C.; Hernández-Sosa, D.; Greiner, D.; Zamuda, A.; Caldeira, R. An Approach to Multi-Objective Path Planning Optimization for Underwater Gliders. *Sensors* **2019**, *19*, 5506. [[CrossRef](#)] [[PubMed](#)]
198. Ma, Y.; Mao, Z.; Wang, T.; Qin, J.; Ding, W.; Meng, X. Obstacle avoidance path planning of unmanned submarine vehicle in ocean current environment based on improved firework-ant colony algorithm. *Comput. Electr. Eng.* **2020**, *87*, 106773. [[CrossRef](#)]
199. Huo, L.; Zhu, J.; Wu, G.; Li, Z. A Novel Simulated Annealing Based Strategy for Balanced UAV Task Assignment and Path Planning. *Sensors* **2020**, *20*, 4769. [[CrossRef](#)]
200. Ni, J.; Wu, L.; Wang, S.; Wang, K. 3D real-time path planning for AUV based on improved bio-inspired neural network. In Proceedings of the 2016 IEEE International Conference on Consumer Electronics-Taiwan (ICCE-TW), Nantou, Taiwan, 27–29 May 2016; pp. 1–2.
201. Xudong, T.; Yongjie, P.; Ye, L.; Zaibai, Q. A fuzzy neural networks controller of underwater vehicles based on ant colony algorithm. In Proceedings of the 2008 27th Chinese Control Conference, Kunming, China, 16–18 July 2008; pp. 637–641.
202. Castillo, O. Bio-inspired optimization of type-2 fuzzy controllers in autonomous mobile robot navigation. In *Advanced Control Techniques in Complex Engineering Systems: Theory and Applications*; Springer: Berlin/Heidelberg, Germany, 2019; pp. 187–200.
203. Lagunes, M.L.; Castillo, O.; Soria, J. Methodology for the optimization of a fuzzy controller using a bio-inspired algorithm. In *North American Fuzzy Information Processing Society Annual Conference*; Springer: Berlin/Heidelberg, Germany, 2017; pp. 131–137.

204. Yu, J.; Liu, J.; Wu, Z.; Fang, H. Depth control of a bioinspired robotic dolphin based on sliding-mode fuzzy control method. *IEEE Trans. Ind. Electron.* **2017**, *65*, 2429–2438. [[CrossRef](#)]
205. Soliman, M.; Azar, A.T.; Saleh, M.A.; Ammar, H.H. Path planning control for 3-omni fighting robot using PID and fuzzy logic controller. In *International Conference on Advanced Machine Learning Technologies and Applications*; Springer: Berlin/Heidelberg, Germany, 2019; pp. 442–452.
206. Li, X.; Choi, B.J. Design of obstacle avoidance system for mobile robot using fuzzy logic systems. *Int. J. Smart Home* **2013**, *7*, 321–328.
207. Li, Y.; Zhu, X.; Liu, J. An Improved Moth-Flame Optimization Algorithm for Engineering Problems. *Symmetry* **2020**, *12*, 1234. [[CrossRef](#)]
208. Ilango, H.S.; Ramanathan, R. A Performance Study of Bio-Inspired Algorithms in Autonomous Landing of Unmanned Aerial Vehicle. *Procedia Comput. Sci.* **2020**, *171*, 1449–1458. [[CrossRef](#)]
209. Tariq, R.; Iqbal, Z.; Aadil, F. IMOC: Optimization Technique for Drone-Assisted VANET (DAV) Based on Moth Flame Optimization. *Wirel. Commun. Mob. Comput.* **2020**, *2020*, 8860646. [[CrossRef](#)]
210. Arantes, M.d.S.; Arantes, J.d.S.; Toledo, C.F.M.; Williams, B.C. A hybrid multi-population genetic algorithm for UAV path planning. In *Proceedings of the Genetic and Evolutionary Computation Conference*, New York, NY, USA, 20–24 July 2016; pp. 853–860.
211. Duan, H.; Luo, Q.; Shi, Y.; Ma, G. ? hybrid particle swarm optimization and genetic algorithm for multi-UAV formation reconfiguration. *IEEE Comput. Intell. Mag.* **2013**, *8*, 16–27. [[CrossRef](#)]
212. Goudos, S.K.; Tsoulos, G.V.; Athanasiadou, G.; Batistatos, M.C.; Zrbouti, D.; Psannis, K.E. Artificial neural network optimal modeling and optimization of UAV measurements for mobile communications using the L-SHADE algorithm. *IEEE Trans. Antennas Propag.* **2019**, *67*, 4022–4031. [[CrossRef](#)]
213. Dong, Z.; Chen, Z.; Zhou, R.; Zhang, R. A hybrid approach of virtual force and Astar search algorithm for UAV path re-planning. In *2011 6th IEEE Conference on Industrial Electronics and Applications*; IEEE: Piscataway Township, NJ, USA, 2011; pp. 1140–1145.
214. Wang, H.; Duan, J.; Wang, M.; Zhao, J.; Dong, Z. Research on robot path planning based on fuzzy neural network algorithm. In *Proceedings of the 2018 IEEE 3rd Advanced Information Technology, Electronic and Automation Control Conference (IAEAC)*, Chongqing, China, 12–14 October 2018; pp. 1800–1803.
215. Zhang, P.; Xiong, C.; Li, W.; Du, X.; Zhao, C. Path planning for mobile robot based on modified rapidly exploring random tree method and neural network. *Int. J. Adv. Robot. Syst.* **2018**, *15*, 1729881418784221. [[CrossRef](#)]
216. Pradhan, B.; Nandi, A.; Hui, N.B.; Roy, D.S.; Rodrigues, J.J. A Novel Hybrid Neural Network-Based Multirobot Path Planning With Motion Coordination. *IEEE Trans. Veh. Technol.* **2019**, *69*, 1319–1327. [[CrossRef](#)]
217. Zhang, S.; Wu, M.; Guo, C. Research on Vision Navigation Technology of Porter Based on Improved Simulated Annealing Algorithms. In *International Conference on Applications and Techniques in Cyber Security and Intelligence*; Springer: Berlin/Heidelberg, Germany, 2019; pp. 642–649.
218. Wang, D.; Chen, S.; Zhang, Y.; Liu, L. Path planning of mobile robot in dynamic environment: Fuzzy artificial potential field and extensible neural network. *Artif. Life Robot.* **2020**, 1–11. [[CrossRef](#)]
219. Zhu, D.; Tian, C.; Sun, B.; Luo, C. Complete coverage path planning of autonomous underwater vehicle based on GBNN algorithm. *J. Intell. Robot. Syst.* **2019**, *94*, 237–249. [[CrossRef](#)]
220. Kumari, S.; Mishra, P.K.; Anand, V. Fault resilient routing based on moth flame optimization scheme for underwater wireless sensor networks. *Wirel. Netw.* **2020**, *26*, 1417–1431. [[CrossRef](#)]
221. Chen, W.; Rahmati, M.; Sadhu, V.; Pompili, D. Real-time Image Enhancement for Vision-based Autonomous Underwater Vehicle Navigation in Murky Waters. In *Proceedings of the International Conference on Underwater Networks & Systems*, Atlanta, GA, USA, 23–25 October 2019; pp. 1–8.
222. Zhu, A.; Yang, S.X. Neurofuzzy-based approach to mobile robot navigation in unknown environments. *IEEE Trans. Syst. Man Cybern. Part C Appl. Rev.* **2007**, *37*, 610–621. [[CrossRef](#)]
223. Dutta, S. Obstacle avoidance of mobile robot using PSO-based neuro fuzzy technique. *Int. J. Comput. Sci. Eng.* **2010**, *2*, 301–304.
224. Obe, O.; Dumitrache, I. Adaptive neuro-fuzzy controller with genetic training for mobile robot control. *Int. J. Comput. Commun. Control* **2012**, *7*, 135–146. [[CrossRef](#)]
225. Jeffril, M.A.; Sariff, N. The integration of fuzzy logic and artificial neural network methods for mobile robot obstacle avoidance in a static environment. In *Proceedings of the 2013 IEEE 3rd International Conference on System Engineering and Technology*, Shah Alam, Malaysia, 19–20 August 2013; pp. 325–330.
226. Juang, C.F.; Chang, Y.C. Evolutionary-group-based particle-swarm-optimized fuzzy controller with application to mobile-robot navigation in unknown environments. *IEEE Trans. Fuzzy Syst.* **2011**, *19*, 379–392. [[CrossRef](#)]
227. Schmidt, K.W.; Boutalis, Y.S. Fuzzy discrete event systems for multiobjective control: Framework and application to mobile robot navigation. *IEEE Trans. Fuzzy Syst.* **2012**, *20*, 910–922. [[CrossRef](#)]
228. Maeda, M.; Maeda, Y.; Murakami, S. Fuzzy drive control of an autonomous mobile robot. *Fuzzy Sets Syst.* **1991**, *39*, 195–204. [[CrossRef](#)]
229. AbuBaker, A. A novel mobile robot navigation system using neuro-fuzzy rule-based optimization technique. *Res. J. Appl. Sci. Eng. Technol.* **2012**, *4*, 2577–2583.

230. Algabri, M.; Mathkour, H.; Ramdane, H. Mobile robot navigation and obstacle-avoidance using ANFIS in unknown environment. *Int. J. Comput. Appl.* **2014**, *91*, Available online: research.ijcaonline.org/volume91/number14/pxc3895400.pdf (accessed on 6 August 2021). [[CrossRef](#)]
231. Mohanty, P.K.; Parhi, D.R. Path planning strategy for mobile robot navigation using MANFIS controller. In *Proceedings of the International Conference on Frontiers of Intelligent Computing: Theory and Applications (FICTA) 2013*; Springer: Berlin/Heidelberg, Germany, 2014; pp. 353–361.
232. Alves, R.M.; Lopes, C.R. Obstacle avoidance for mobile robots: A hybrid intelligent system based on fuzzy logic and artificial neural network. In *Proceedings of the 2016 IEEE International Conference on Fuzzy Systems (FUZZ-IEEE)*, Vancouver, BC, Canada, 24–29 July 2016; pp. 1038–1043.
233. Zhou, Y.; Er, M.J. Self-learning in obstacle avoidance of a mobile robot via dynamic self-generated fuzzy Q-learning. In *Proceedings of the 2006 International Conference on Computational Intelligence for Modelling Control and Automation and International Conference on Intelligent Agents Web Technologies and International Commerce (CIMCA'06)*, Sydney, Australia, 28 November–1 December 2006; p. 116.
234. Jouffe, L. Fuzzy inference system learning by reinforcement methods. *IEEE Trans. Syst. Man Cybern. Part C Appl. Rev.* **1998**, *28*, 338–355. [[CrossRef](#)]
235. Er, M.J.; Deng, C. Online tuning of fuzzy inference systems using dynamic fuzzy Q-learning. *IEEE Trans. Syst. Man Cybern. Part B (Cybern.)* **2004**, *34*, 1478–1489. [[CrossRef](#)]
236. Lagisetty, R.; Philip, N.; Padhi, R.; Bhat, M. Object detection and obstacle avoidance for mobile robot using stereo camera. In *Proceedings of the 2013 IEEE International Conference on Control Applications (CCA)*, Hyderabad, India, 28–30 August 2013; pp. 605–610.
237. Fulgenzi, C.; Spalanzani, A.; Laugier, C. Dynamic obstacle avoidance in uncertain environment combining PVOs and occupancy grid. In *Proceedings of the 2007 IEEE International Conference on Robotics and Automation*, Rome, Italy, 10–14 April 2007; pp. 1610–1616.
238. Michels, J.; Saxena, A.; Ng, A.Y. High speed obstacle avoidance using monocular vision and reinforcement learning. In *Proceedings of the 22nd International Conference on Machine Learning*, Bonn, Germany, 7–11 August 2005; pp. 593–600.
239. Matveev, A.S.; Hoy, M.C.; Savkin, A.V. A globally converging algorithm for reactive robot navigation among moving and deforming obstacles. *Automatica* **2015**, *54*, 292–304. [[CrossRef](#)]
240. Seraji, H.; Howard, A. Behavior-based robot navigation on challenging terrain: A fuzzy logic approach. *IEEE Trans. Robot. Autom.* **2002**, *18*, 308–321. [[CrossRef](#)]
241. Sharma, P.S.; Chitaliya, D. Obstacle avoidance using stereo vision: A survey. *Int. J. Innov. Res. Comput. Commun. Eng.* **2015**, *3*, 24–29. [[CrossRef](#)]
242. Typiak, A. Use of laser rangefinder to detecting in surroundings of mobile robot the obstacles. In *Proceedings of the Symposium on Automation and Robotics in Construction*, Vilnius, Lithuania, 26–29 June 2008; pp. 26–29.
243. Baldoni, P.D.; Yang, Y.; Kim, S.Y. Development of efficient obstacle avoidance for a mobile robot using fuzzy Petri nets. In *Proceedings of the 2016 IEEE 17th International Conference on Information Reuse and Integration (IRI)*, Pittsburgh, PA, USA, 28–30 July 2016; pp. 265–269.
244. Yang, J.; Chen, P.; Rong, H.J.; Chen, B. Least mean p-power extreme learning machine for obstacle avoidance of a mobile robot. In *Proceedings of the 2016 International Joint Conference on Neural Networks (IJCNN)*, Vancouver, BC, Canada, 24–29 July 2016; pp. 1968–1976.
245. Haykin, S.; Network, N. A comprehensive foundation. *Neural Netw.* **2004**, *2*, 41.
246. Sun, B.; Han, D.; Wei, Q. Application of Rolling Window Algorithm to the Robot Path Planning. *Comput. Simul.* **2006**, *23*, 159–162.
247. Syed, U.A.; Kunwar, F.; Iqbal, M. Guided Autowave Pulse Coupled Neural Network (GAPCNN) based real time path planning and an obstacle avoidance scheme for mobile robots. *Robot. Auton. Syst.* **2014**, *62*, 474–486. [[CrossRef](#)]
248. Al-Mutib, K.; Abdessemed, F.; Faisal, M.; Ramdane, H.; Alsulaiman, M.; Bencherif, M. Obstacle avoidance using wall-following strategy for indoor mobile robots. In *Proceedings of the 2016 2nd IEEE International Symposium on Robotics and Manufacturing Automation (ROMA)*, Ipoh, Malaysia, 25–27 September 2016; pp. 1–6.
249. Ahmed, A.A.; Abdalla, T.Y.; Abed, A.A. Path planning of mobile robot by using modified optimized potential field method. *Int. J. Comput. Appl.* **2015**, *113*, 6–10. [[CrossRef](#)]
250. Gul, F.; Mir, I.; Rahiman, W.; Islam, T.U. Novel Implementation of Multi-Robot Space Exploration Utilizing Coordinated Multi-Robot Exploration and Frequency Modified Whale Optimization Algorithm. *IEEE Access* **2021**, *9*, 22774–22787. [[CrossRef](#)]
251. Gul, F.; Mir, I.; Abualigah, L.; Sumari, P. Multi-Robot Space Exploration: An Augmented Arithmetic Approach. *IEEE Access* **2021**, *9*, 107738–107750. [[CrossRef](#)]
252. Cherroun, L.; Boumehraz, M.; Kouzou, A. Mobile Robot Path Planning Based on Optimized Fuzzy Logic Controllers. In *New Developments and Advances in Robot Control*; Springer: Berlin/Heidelberg, Germany, 2019; pp. 255–283.
253. Chhotray, A.; Parhi, D.R. Navigational control analysis of two-wheeled self-balancing robot in an unknown terrain using back-propagation neural network integrated modified DAYANI approach. *Robotica* **2019**, *37*, 1346–1362. [[CrossRef](#)]
254. Burchardt, H.; Salomon, R. Implementation of path planning using genetic algorithms on mobile robots. In *Proceedings of the 2006 IEEE International Conference on Evolutionary Computation*, Vancouver, BC, Canada, 16–21 July 2006; pp. 1831–1836.

-
255. Su, K.; Wang, Y.; Hu, X. Robot path planning based on random coding particle swarm optimization. *Int. J. Adv. Comput. Sci. Appl.* **2015**, *6*, 58–64. [[CrossRef](#)]
 256. Karaboga, D.; Gorkemli, B.; Ozturk, C.; Karaboga, N. A comprehensive survey: Artificial bee colony (ABC) algorithm and applications. *Artif. Intell. Rev.* **2014**, *42*, 21–57. [[CrossRef](#)]