Review of wheeled mobile robot collision avoidance under unknown environment

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Abstract

Recently, the working scenes of the robot have been emerging as diversity and complexity with gradually mature of robotic control technology. The challenge of robot adaptability emerges, especially in complicated and unknown environments. Among the numerous researches on improving the adaptability of robots, aiming at avoiding collision between robot and external environment, obstacle avoidance has drawn much attention. Compared to the global circumvention requiring the environmental information that is known, the local obstacle avoidance is a promising method due to the environment is possibly dynamic and unknown. This study is aimed at making a review of research progress about local obstacle avoidance methods for wheeled mobile robots (WMRs) under complex unknown environment in the last 20 years. Sensor-based obstacle perception and identification is first introduced. Then, obstacle avoidance methods related to WMRs’ motion control are reviewed, mainly including artificial potential field (APF)-based, population-involved meta heuristic-based, artificial neural network (ANN)-based, fuzzy logic (FL)-based and quadratic optimization-based, etc. Next, the relevant research on Unmanned Ground Vehicles (UGVs) is surveyed. Finally, conclusion and prospection are given. Appropriate obstacle avoidance methods should be chosen based on the specific requirements or criterion. For the moment, effective fusion of multiple obstacle avoidance methods is becoming a promising method.

Keywords

Wheeled mobile robots, obstacle avoidance, survey

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Introduction

Intelligent robots, which are committed to saving people from repetitive, onerous, or dangerous tasks, have received compelling attention from academia and industry due to its wide application.\(^1\) Advances in intelligent technologies, especially in artificial intelligence, computer vision, Internet of things, and wireless communication, have greatly contributed to rapid development and success of robotic applications. With gradually mature of robotic control technology, simultaneously, the working scenes of the robot have been emerging as diversity and complexity.\(^2\) Complicated or dangerous tasks such as deep sea exploring, pipeline inspection, fruit or vegetable picking and fire fighting, etc., impose a challenge on adaptability of the robot.

Mobility and manipulation are two major functional requirements for robots. In terms of functionality, robots are divided into mobile robots, robot manipulators, and mobile manipulators with both mobility and manipulation. The manipulator is usually designed as a series of links connected by motor-driven joints which extend from a fixed base to an end-effector\(^3,4\) whose workspace is limited. Compared to the manipulator, mobile robots are more flexible and have wider movement range. Among mobile robots, wheeled mobile robots (WMRs) are common and widely used.\(^5\) Different working environments need different types of robot. Merely, no matter what kind of robot it is, negative influence of the obstacle on the effectiveness of mission execution can not be ignored during a robot executes a desired task in an environment with obstacles. An effective obstacle avoidance method is necessary and should be incorporated inside motion planning controller of robots.

Obstacle avoidance motion planning is to find a collision-free desirable motion path for a robot to reach the goal in its working environment with static or moving obstacles.\(^6\) Motion planning, which is the basis of robot control, has been the subject of numerous studies recent. Quite a few products toward applications and improvements have been reported such as Refs.\(^7\)–\(^10\) In order to make the robot complete the desired tasks effectively and accurately, and meanwhile avoid collision with the encountered obstacles, many collision avoidance methods have been proposed. Generally speaking, the obstacle avoidance method can be divided into two classes: global and local methods. Well-known \(A^*, D^*,\) rapidly-exploring random tree (RRT), and probabilistic roadmaps (PRM)\(^11\) algorithms are global planning methods. The difference is that the first two are search-based-planning methods. RRT and PRM are sampling-based-planning method. These methods usually need global information of the current environment, especially positions of both the target and obstacles. Therefore, global planning methods do not fit in dynamic and unknown environments, and are universally with high computational cost. Compared to global planning, local planning methods are provided with low computational complexity. When the environment changes, local planning methods could adjust control commands rapidly to adapt to the new environment. Typical local planning methods include artificial potential field (APF)-based algorithm, population-involved meta-heuristic-based algorithm such as genetic algorithm (GA), particle swarm optimization (PSO), ant colony optimization (ACO),\(^12\) and beetle antenna search (BAS), etc., artificial neural network (ANN) based
algorithm and fuzzy logic (FL) based ones, etc. In current study, we are aimed at making a review of research progress about local obstacle avoidance methods for WMRs only with mobility under complex unknown environment in the last 20 years. The section structure of this paper is arranged around the following aspects. After introduction, sensor-based obstacle perception and identification technology is introduced. Then, collision avoidance methods applied to WMRs are reviewed. Next section shows the relevant research on Unmanned Ground Vehicles (UGVs). Finally, this research is summarized, and prospection is also given.

**Obstacle perception and identification**

Obstacle sensing and identification are the prerequisite of achieving collision-free motion planning for robots. According to the collision avoidance process, robot collision avoidance consists of three parts:

- **Obstacle perception:** The robot senses its surrounding obstacles that may affect its motion through the equipped environment sensing system consisting of various sensors. At present, the widely used sensors are vision-based sensors and ranging sensors such as the ultrasonic sensor, the infrared sensor, the laser sensor. Among the vision-based sensors, monocular vision and binocular vision are widely used. Table 1 summarizes their principles, advantages, and disadvantages of these sensors.

- Each type of sensor has its own principle and characters. However, no sensor is applicable for any environment perfectly. Nowadays, in practical application, obtaining environmental information favors from multi-type sensors fusion.\(^{13-15}\) Merely, this also increases the complexity and difficulty of information processing owing to information sensed by different sensor needed to be integrated. There are also some researchers casting light to other types of sensors. Sifuentes et al.,\(^{16}\) a vehicle detector intended for a wireless sensor network is developed, which consists of a magnetic sensor and an optical sensor which is used to detect the vehicle shade.

- Robots senses the surrounding environment relying on sensors, admittedly, the challenge resulted from perception latency emerges, especially for high-speed robots in cluttered, unknown environments. Perception latency refers to the time required by a robot that senses the environment and processes the captured data to generate control commands. The higher the relative speed between the robot and the obstacle, the faster detect speed is required to generate a safe maneuver to avoid collision. Latencies of tens or hundreds of milliseconds are common in current robots.\(^{17}\) Literature\(^{18-20}\) cast light on camera-based low latency localization solution. For perception latency tolerance in a navigation task,\(^{21}\) proposes a framework to predict and compensate for the latency between sensing and actuation in a robotic platform\(^{17}\) highlights the influence of latency on the performance of high-speed navigation, showing how the maximum latency the robot can tolerate to guarantee
safety, which is related to the desired speed, the agility of the platform in this research.

- **Collision decision:** Decide collision probability between the robot with the detected obstacles based on certain criteria.
- After determining the position and size of the obstacle, the robot requires deciding whether it would collide with the detected obstacle based on certain
criteria. These criteria can be that: such as, always keep a safe distance between the robot and all obstacles. The safe distance is usually determined by the user. If the distance between a robot and a detected obstacle is less than the defined safety distance, the collision criterion will be decided to be satisfied, so that the collision avoidance mechanism is activated and top-priority in control task.

- **Collision avoidance:** Collision avoidance mechanism would be activated to help the robot escape the obstacle if the collision criterion is satisfied.

### Collision avoidance methods

In this part, we selectively review some reported literature related to collision avoidance of WMRs in the last 20 years. Positions, sizes, and shapes of obstacles are assumed to be known with help of various sensors reviews obstacles avoidance methods related to mobile robots navigation in static unknown environment. Relevant researches in agriculture are surveyed in Gao et al. The related literatures mentioned in Shitsukane et al. and Gao et al. are thus not introduced again.

#### APF-based

The APF-based method is first proposed by Khatib, where the robot is assumed to move in a virtual potential field consisting of the attractive potential field and the repulsive potential field. The target is described as an attractive force, and the obstacle is described as a repulsive force. The resultant force is used to decide the next direction of the robot in motion planning.

The APF-based method is simple, convenient to implement. Merely, it is also easy to fall into the local optimum and with many limitations. Many applications of the APF-based method to the mobile robot navigation have been reported. A large number of conference papers in the proceedings are explicitly devoted to application of the improved APF-based method. Aiming at the drawback that the original APF-based method is easy to trap into the local minimum, simulated annealing algorithm is together used with the basic APF method in Park et al. Only when the basic APF falls into the local minimum, the simulated annealing algorithm will come into force. In Shi et al., an improved APF algorithm is proposed for obstacle avoidance of mobile robots by building a new potential force function. The presented method can avoid the robot trapping into the local minimum and mitigate the vibrating problem arising in the original APF. An obstacle avoidance method based on a gravity chain is proposed in Tang et al. In this method, it is supposed that there is a rubber band whose beginning connects with its ending in potential field around obstacle. By putting effective obstacle avoidance information into potential field through a gravity chain, the problem that the original APF-based method often converges to local minima is solved. Different from
the basic APF, the potential force does not directly act on the robot. Therefore, the problems that the robot cannot reach the target when the obstacle is near the target, as well as oscillation are also solved. Focusing on the non-reachable problem in a situation that the obstacle is near the target, an improved APF is proposed in Li et al.\textsuperscript{28} Specially, a regulative agent is introduced into the potential field. The attraction will be reduced as a linear function when the robot is close to the target, the repulsion is decreased as a higher-order function.

The original APF-based method is devoted to give a feasible collision-free path from the source to the target. To generate the shortest/approximately shortest path, a regression search method is developed in Li et al.\textsuperscript{29} to optimize the path planned by the APF-based method. Potential functions are redefined, virtual local target and repulsive force disappearance as well as circle tangential line of circle are utilized to eliminate oscillations, local minima, and non-reachable problems. In this paper, environmental information is known completely.

Extended to multiple robots from a mobile robot, the study\textsuperscript{30} considers the formation control problem of a group of non-holonomic mobile robots where every WMR moves along the predefined trajectory while maintaining a geometric formation in a 2D environment. The APF method is applied to bypass the collision with the obstacles before the robots reach the goal point. To avoid falling into local minimum, rotating fields are defined around obstacles. For a rectangular obstacle, an ellipse is defined around it whose field matches the direction of approaching robot. However, whether the collision avoidance refers to the collision with the environmental obstacles or with other team members working in a shared environment is not mentioned clearly in this paper. In Yang et al.,\textsuperscript{31} leader-follower-based formation control problem with collision, obstacle avoidance, and connectivity maintenance is considered for a class of second-order nonlinear multi-agent systems under external disturbances, where the APF method is used to achieve collision, obstacle avoidance. Attractive field function takes formation maintenance problem of multi-agents during they avoid obstacles into account. Instead of dealing with nonlinear dynamics of agents and environmental disturbances separately, in this paper, neural network technology is employed to approximate both collectively by treating nonlinear dynamics and unknown disturbances as a dynamics set. In this way, triangle formation maintenance and collision-free motion planning are achieved, and the system is robust to external disturbances.

Among most works related to mobile robot obstacle avoidance based on the APF, the position of the obstacle is usually assumed to be fixed. For dynamic obstacles, the concept of collision time is introduced into the potential function in Li et al.\textsuperscript{32} which takes the relative velocity of the obstacle to the robot and the collision angle into account. An artificial neural network is used to predict the position and velocity information of the obstacle, which is trained by previous positions of the obstacle.

Table 2 gives comparison between the above-mentioned APF-based literatures. In summary, the inherent drawbacks of the basic APF method are mainly improved by researchers from two aspects: (1) designing a new potential field function; (2)
integrating it with other advanced methods. For the first method, different scenarios usually need to design different potential field functions. Apart from solving the problem of local optimum and oscillation arising in the traditional APF method by improving the potential field function, control algorithms that are based on a quantity called danger field are proposed to achieve safety control for manipulators in a human-robot interaction environment in Kulic’ and Croft\textsuperscript{33} and Lacevic et al.\textsuperscript{34} The main principle behind the danger field-based approach is to reduce the danger index during the robot motion to ensure safety by generalizing several danger indices into the robot safety-assessment\textsuperscript{34} considers the kinematic state of the manipulator as a whole and indicates how dangerous the current posture and velocity of the robot are to the objects in the environment in comparison with Kulic’

| Table 2. Comparison between the above-mentioned APF-based literatures. |
|-----------------------------|---------------------|-------------------|-----------------|-----------------|
| Literatures     | Problems to be solved | WMRs number | Methods | Advantages | Improvements |
| Park et al.\textsuperscript{25} | Navigation | Single | Simulated annealing &0x002B; the APF | Improve performance of the original APF that is easy to trap into the local minimum | Improve the vibrating problem | Improve the target non-reachable problem | Is a feasible path |
| Shi et al.\textsuperscript{26} | Navigation | Single | Improve potential function | Introduce gravity chain concept into the APF | Improve the target non-reachable problem | Is a feasible path |
| Tang et al.\textsuperscript{27} | Navigation | Single | Regression search &0x002B; the APF | Improve the target non-reachable problem | Is the shortest path from source to target | Environmental information is known completely. | Not clearly mention collision avoidance objects |
| Li et al.\textsuperscript{29} | Navigation | Single | Introduce rotating fields into the APF | Improve local minimum performance | Consider connectivity maintenance during collision avoidance | Not inter-robots consider collision avoidance |
| Azhar and Bilal Kadri\textsuperscript{30} | Formation | Multiple | Introduce rotating fields into the APF | Improve local minimum performance | Consider connectivity maintenance during collision avoidance | Not inter-robots consider collision avoidance |
| Yang et al.\textsuperscript{31} | Formation | Multiple | Introduce collision time concept into the APF | Avoid dynamic obstacles | Only consider single WMR | |
| Li et al.\textsuperscript{32} | Navigation | Single | Introduce collision time concept into the APF | Avoid dynamic obstacles | Only consider single WMR | |
and Croft. Except the danger field based on field concept, another field method, that is, artificial coordinating field method, has also been proposed and has been found its application in safety planning of mobile robots.

**Population-involved meta heuristic-based**

The APF-based method shows weakness in a dynamic environment with moving obstacles. Intelligent obstacle avoidance methods such as GA-based, neural network-based, fuzzy logic-based are receiving compelling attention to achieve collision-free of mobile robots in a dynamic environment. Population-based meta-heuristic search algorithms, inspired by the social behavior of nature, are of great concern for a long time. They are with several advantages: for example, the implementation is simple and easy, and the algorithm can bypass local optimum, the shortest path generation, etc. Motivated by their advantages, nowadays population-based meta-heuristic algorithms have been found their application in the collision-free motion planning problem of mobile robots.

A fixed solution length bit sequence is adopted in the traditional GA. In Kala et al., representation of a graphical node that is considered as a chromosome is proposed, which is effective for all sorts of highly chaotic conditions with multiple obstacles. In Elhoseny et al., an GA-based dynamic path planning method is proposed where the environment is monitored by a wireless sensor network, the movement path of the robot is updated by receiving a signal from a base station based on alerts that are periodically triggered by sensors. Bezier Curve is used to refine the final path based on the control points identified by the GA-based dynamic path planning method. Apart from avoiding the environmental obstacles successfully, the method reduces the time required to get the optimum path by 6% up to 47%. The path smoothness is also improved in the range of 8% and 52% based on the reported results.

A chaos-GA-integrated hybrid algorithm with adaptive and floating-point code is proposed in Gao et al., and is applied to the path planning of a mobile robot. The hybrid algorithm has higher accuracy and faster convergence speed than the basic GA, and the generated path is the shortest path from the source to the target. In hybrid GA proposed in Zhang et al., the grid method is used to model the working environment of a mobile robot, the digital potential field is used to generate initial path population, and different fitness functions of feasible and unfeasible paths are also adopted, accelerating the convergence of the algorithm and improving the accuracy. The deleted and inserted operators are added in the GA, achieving the requirement of collision avoidance with the obstacle. An improved GA-based path planning scheme is proposed in Shi and Cui for collision-free navigation of a mobile robot under unknown environment. Compared to the conventional GA, the real coding with low computational complexity and the reduced search space, a fitness function considering the collision avoidance path, the shortest distance, and smoothness of the path, specific genetic operators are devised in the improved GA.
The presented GA is verified that it is effective under various complex and dynamic environments.

PSO-based collision-free motion planning algorithm for single robot in a rough terrain environment is proposed in Wang et al.\textsuperscript{43} In the proposed algorithm, a crowding radius-based position updating method is adopted in the global optimal position updating formulation, and the non-uniformity factor is used to update the position of particles when the path collides with obstacles. This way contributes to the efficiency of the original PSO method and population diversity. However, the simulation test is conducted in a static and known rough terrain environment. In Dadgar et al.,\textsuperscript{44} and Das et al.\textsuperscript{45} PSO is used for collision avoidance motion planning of multiple mobile robots. In Dadgar et al.,\textsuperscript{44} PSO algorithm is employed in multiple robots target searching optimization task performing in an unknown environment. The algorithm has good performance for small robot population and single-target searching task. The multi-targets searching problem is not involved in this study\textsuperscript{45} proposes a hybrid optimization algorithm (IPSO-DV) that combines an improved PSO (IPSO) with differentially perturbed velocity (DV), to determine an optimal path for multi-robots in a clutter environment. The main idea of the IPSO-DV algorithm is to adjust the velocities of the particles in IPSO with a vector differential operator borrowed from DE family. In this study, the environment and obstacles are static, the dynamic environmental obstacles are not considered. Except GA, PSO, a combination of these algorithms or a combination of them and other obstacle avoidance algorithms have also been applied to the mobile robot navigation. An overview of application of these algorithms in mobile robot navigation can be found in Pandey.\textsuperscript{46}

In above-mentioned biological inspired algorithms, a great number of particles are usually needed to generate the shortest path. Beetle antennae search (BAS) algorithm,\textsuperscript{47} is inspired by the foraging principle of beetle, incrementally arises as a promising solution. The algorithm is of great concern due to its fast convergence speed, and it only need a particle in the optimal path generation. In Khan et al.,\textsuperscript{48} BAS-based control strategy is proposed for simultaneous tracking control and obstacle avoidance of a redundant manipulator, where the tracking control and obstacle avoidance problem is unified as a single optimization function by a penalty term. Utilizing the BAS algorithm, the KUKA LBR IIWA-14 seven degree of freedom (DOF) manipulator successfully avoids an arbitrarily shaped environmental obstacle in front of it while following the desired path. However, there is no application of this method in obstacle avoidance motion planning of mobile robot.

**Neural network-based**

Artificial Neural network is a kind of nonlinear computing model composed of a large number of inter-connected neurons, which can model the complex relationship between input and output variables. The neural network-based path planning method is usually to establish a neural network model related to the movement path of the robot from the source to the target. The input of the model usually is
sensor information, previous position of the robot, or the previous movement direction. Commands of next position and direction are output by training the model. Neural networks are widely used in control of uncertain systems due to their high approximation capabilities.49

An application of ANN in mobile robot navigation under dynamic unknown environment is also achieved in Kala et al.38 It is concluded that compared to the ANN, the GA takes more time in terms of path generation. For the ANN-based path planning method, the overall path number traveled by the robot is less compared to the GA-based method. However, the ANN method will fail in a highly chaotic environment. Merely, the memory requirement for the GA is very high in comparison with the ANN.

A backward ANN is applied to the movement control of a mobile robot under a dynamically changing environment with the moving obstacle in Zarate et al.50 The ANN structure considers the past position and the future position at the same time. Past positions provide the ANN with memories of the mobile robot previous positions. Future position provides the ANN with a goal that the robot would go next. The advantage is that the robot can adaptively predict the next coordinates.

In Hu et al.,51 pedestrian collision avoidance problem is considered during the mobile robot navigation. Two deep neural networks are used to achieve pedestrian avoidance and path following tasks respectively. Neural networks are trained with images labeled with movement decisions. The training process is end-to-end, and requires less time in labeling. For image labeling, computer vision-based labeling technology and a monocular RGB camera based one are used for comparison. In terms of static obstacles avoidance, ultrasonic sensor is used. Experiments results verify that the deep learning method using a RGB camera is more robust compared to the computer vision-based.

In Guan et al.,52 an interval type-2 fuzzy neural network is designed for the wheeled mobile robot to achieve obstacle avoidance smoothly and position stabilization. In the presented method, membership functions are redefined through the addition of the uncertain means and standard deviation, and fuzzy sets are used as membership values, reducing the effect of uncertainties. An WMR can follow a shorter path from the source to the target and achieve smoother movement during obstacle avoidance based on the presented neural network method.

In Huang et al.,53 a neural network-based Q-learning architecture is developed for an autonomous mobile robot. Q-learning algorithm is used to learn obstacle avoidance experience online through samples collecting from interaction with the real environment. A three-layer Back-Propagation neural network trained by the error back propagation algorithm is used to store the $Q$ values. The presented method does not need the complete knowledge around the external environment and can learn online. Therefore, the robot can adaptively tune itself behavior to react complex, unknown, and dynamic working environment.

A modified pulse-coupled neural network method is proposed in Qu et al.54 to generate a collision-free path for a mobile robot under a dynamic environment. The proposed neural network is topologically organized with only local lateral
connections among neurons. The method requires no prior knowledge of target or obstacles, and can give the shortest path from the source to the target. The computational complexity of the proposed algorithm is only related to the length of the generated shortest path. However, a weakness is that global knowledge of the current environment is assumed to be available, which is not very realistic in real applications.

In Wang et al., a distance-based spiking neural network (SNN) behavior controller is designed for WMRs using ultrasonic sensory information, where unsupervised spike-based Hebbian learning algorithm is used to train the SNN. Compared with the classical NNs, the SNN has better robustness to noise and is easy to model. Merely, due to its output is pulses, the gradient-decent-based learning rules cannot be employed to SNN directly. In this study, SNN-based controller achieves collision avoidance motion planning with less neurons compared to the traditional NNs. The SNN is further extended to mobile robot navigation solution in Wang et al., a behavior-based modular navigation controller is proposed. The controller does not need accurate the environment information, and is suitable to unknown and unstructured environments.

Above-mentioned works focus on the nonlinear control of single mobile robot. In Li et al., a neural-network-based approach is proposed for a multi-robots system with moving obstacles. Simulation results show that the developed intelligent controller is able to generate collision-free paths for multiple robots in a workspace with moving obstacles. Leader-follower based formation control problem of multiple mobile robots is considered in Dierks and Jagannathan. Treating other robots in a shared environment as obstacles, the whole formation is also asymptotically stable during the obstacle avoidance by applying robust integral of the sign of the error method. The region reaching formation control problem for multi-robot systems is considered in Yu et al. neural networks are trained online, and are use to approximate the robotic dynamics model uncertainties and external disturbances, without requiring any preliminary off-line training. A feed-forward neural network is used to learn the unknown dynamics. An adaptive control gain law combined with the RBF neural network is derived, which is used to adjust the weight of the control task. The developed NNs-based control scheme is a distributed control strategy, the desired formation does not entirely depend on the objective region and effect caused by the model uncertainties and external disturbances can be suppressed by the designed robust compensator. The formation control solution of multi-agent system in the presence of heterogeneous communication delays is discussed in Guo et al. A continuous repulsive APF is incorporated into agents’ velocities to avoid collision. The radial basis function neural networks (RBFNNs) based adaptive control method is proposed to ensure the robustness against model uncertainties, disturbances, and communication delays. In Yu et al. and Guo et al. illustrating example only gives the simulation result corresponding to the fixed environmental obstacle. In Wang et al., reinforcement learning based duel neural network is employed to control multi-robot coordination behavior. Only image as input, the neural network is trained by learning the actions of each robot.
The end-to-end deep reinforcement learning is used, where negative rewards are set if collisions between multiple robots and obstacles occur. If the robot does not collide or that the robot reaches the target point, the reward will be positive. Reinforcement learning algorithms are trained based on robots’ own experience, unlike supervised learning that learn from human expert knowledge. Moreover, a great quantity of dataset samples are usually required for supervised learning method. The combination of reinforcement learning and the deep neural network shows a powerful performance, such as well-known AlphaGo\textsuperscript{62} and AlphaGo Zero\textsuperscript{63} that win the human Go champion in Go games. Except reinforcement learning, the combination of broad learning and neural network is also showing a potentiality.\textsuperscript{64,65}

Neural network model can learn, and model linear, nonlinear and complex relationships. In the last years, robot skill learning is receiving the compelling attention. Through the accumulation of prior knowledge, robots are expected to generate new knowledge and experience so that it can autonomously make decisions or obtain behavior guidance in a complex environment. There are a lot of related works that have been reported, for example,\textsuperscript{66–70} Neural network-based robot skill learning will be an important development direction of robots in the future. In addition, among NN-based methods, a fact that a quantity of data need to be trained is also indisputable.

**Fuzzy logic-based**

The concept of FL is introduced by Zadeh,\textsuperscript{71} which is inspired by human reasoning. Fuzzy systems can handle uncertainty and imprecise information using linguistic rules. FL-based method provides an effective way for obstacle avoidance, which contains a fuzzy rule base that is constructed and tuned by a human expert. Fuzzy systems can handle uncertainty and imprecise information using linguistic rules. Fuzzy logic control is widely used for mobile robot navigation, this is mainly due to it can offer inference using environmental data, even under motion and sensor uncertainties.\textsuperscript{72}

In Li and Yang,\textsuperscript{73} a vision-based landmark recognition system is developed for mobile robot navigation. A GA-based search method for pattern recognition of digital images is proposed to recognize artificial landmarks by searching all the predefined patterns. A combination of eight ultrasonic sensors is designed to achieve collision-free through a set of fuzzy rules. An FL-based online robot navigation method is investigated in Faisal et al.\textsuperscript{74} for mobile robots under a unknown dynamic environment. The authors introduces how to use two fuzzy logic controllers for achieving the target tracking control and collision avoidance of robots, respectively.

WMRs usually work a dynamic and unknown environment. The uncertainties of environment and the insufficient information on the environment impose challenges on robotic control. To addressing these challenges, controller design that combines both learning with reasoning abilities becomes popular in the few years.
Neuro-fuzzy controllers integrate the advantages of neural network and fuzzy logic control.\textsuperscript{64}

Behavior-based control approach for mobile robots navigation refers to that a complex navigation task is decomposed as several behaviors which are easy to design and perform. In Song and Lin,\textsuperscript{72} the robot navigation task is decomposed as three primary behaviors that are obstacle avoidance, wall following, and goal seeking. These three behaviors are implemented by using fuzzy logic methods. A neural network architecture is proposed for determining the fuzzy weight of every behavior. Neural network is used to map the environmental information sensed by sensors to choose suitable fusion weights. However, it is observed from the experimental results that the robot does not reach the desired goal position with some errors.

In Wen,\textsuperscript{75} Elman neural network and fuzzy logic integrated control algorithm is proposed to enhance the performance of the robot in obstacle avoidance. A virtual force field is built between the robot and obstacles by the hybrid force/position algorithm. Using Elman neural network to compensate uncertainty effect of the dynamic model of the WMA, and which is integrated with the fuzzy control method to self-tune the exact distance between the WMR and the obstacle online. Further application of the method proposed in Wen can be found in Yang et al.\textsuperscript{76} In Zhu and Yang,\textsuperscript{77} neuro fuzzy-based method is integrated for the WMR under unknown environment. A fuzzy logic system with both target tracking and obstacle avoidance performances is designed. Two neural network-based learning algorithms are developed, they are used to tune the parameters of membership functions and suppress redundant fuzzy rules, respectively. A neuro-fuzzy system with mixed supervised learning and reinforcement learning usage is proposed in Ye et al.\textsuperscript{78} Supervised learning method is used to determine the membership functions for the input and output variables simultaneously. After training, reinforcement learning algorithm is employed to fine-tune the membership functions for the output variables. The learning ability is enhanced by improving Sutton and Barto’s model. A virtual environment simulator is developed to obtain data that is used to train the neural fuzzy system.

In these above-mentioned works, they only reconsidered collision avoidance with environmental obstacles. In Pandey,\textsuperscript{79} the safe-navigation problem of multiple WMRs is investigated under unknown cluttered environment. An adaptive neuro-fuzzy control system integrated ANN and fuzzy logic technology is developed, in which the front, left, and right obstacle distances are chosen as control input. The steering angle is determined as the control variable to control the movement of the robot. Under the proposed control system, the generated path for the robot is smooth and optimal, and every robot could achieve the environmental obstacle avoidance, robot inner-collision avoidance, and the goal seeking behaviors. Literature\textsuperscript{80} proposes a hybrid rule-based-neuro-fuzzy controller with rules incorporating the desired motion and direction, distances between WMRs and obstacles/targets. The collision-free during motion planning is achieved by combining a repelling influence between WMRs and nearby obstacles with an attracting
influence between WMRs and targets. As control variables, appropriate heading angle is output. The proposed controller improves navigation performance of multiple WMRs in complex and unknown environments. In Pradhan et al., FL-based navigation performance is investigated for WMRs as many as 1000 in a totally unknown environment. For comparison, fuzzy logic controllers using different membership functions are developed. A conclusion is obtained that controller with Gaussian membership function is most efficient for WMRs navigation. For Pandey, and Parhi et al. the heading angle is used as control variable. However, the considered environmental obstacle is static in Pandey, and every robot independently moves along the generated traveling path without considering the communication between robots. For online interaction, connectivity problem of multiple WMRs network should be addressed.

**Constrained optimization-based**

Recently, some scholars try to address the problem of mobile robot motion control from the perspective of constraint optimization. The basic idea of this class of method can be described as: the collision avoidance strategy is formulated as an inequality equation that is related to the safety threshold, which is treated as a constraint and is attached to the robot’s kinematic control scheme. By describing the control scheme as a quadratic programming (QP) minimization problem, the optimization technology is then used to resolve it online. An obvious advantage of this method is that multiple control goals such as collision avoidance, robot inherent physical limits, target tracking, and so on, can be achieved simultaneously. Physical constraints compliance can further ensure the safety and system stability of robots.

At first, this method was mainly used to address the redundant resolution problem of the robot manipulator. In the reported works, multi-objectives integrated hybrid tasks are usually unified as a time-varying QP minimization optimization problem, where the inverse kinematics of the manipulator is described as an equality equation, and the obstacle avoidance problem is formulated as an equality or inequality equation which is universally solved in velocity level or acceleration level. In references, the obstacle avoidance problem is formulated as an inequality constraints. An obstacle avoidance scheme that is formulated as an equality constraint is proposed in Tang et al. In their works, basic idea of the obstacle avoidance strategy is that the distance between the manipulator and an obstacle is described as point-to-point distance based on the mathematical geometric. By ensuring that the distance vector keeps outside a safety threshold, the collision-free is guaranteed. Obstacle avoidance inequality is solved in velocity level in references compared to references that are solved in acceleration level. In Guo and Zhang, Chen and Zhang inner and outer safe thresholds are considered. In addition, the manipulator is simplified as a set of points by uniformly choosing point in links of the manipulator in Xu et al. For this method, one possibility is that the chosen point does not collide with the obstacle,
in fact the nearest component on the manipulator to the obstacle has collided with the obstacle. To overcome this drawback,\textsuperscript{91} gives an improved obstacle avoidance scheme which can return the nearest point on the manipulator to the obstacle by utilizing vector relations between the geometric elements.

The above mentioned works only consider collision avoidance between the single manipulator and the environmental obstacles. Extending from single manipulator to multiple manipulator increases the computational complexity of the control algorithm. How to communicate each other and share information in a shared environment imposes a challenge on robotic control. QP-based cooperative kinematic control problem of multiple redundant manipulator in a shared workspace are investigated in references.\textsuperscript{4,89,95–97} To mitigate influence of environment inference or signal loss on accuracy of the desired task achieved by the manipulator, control schemes with inherent noise-resistant are introduced in references.\textsuperscript{82,98,99} However, there are few works that are devoted to collision avoidance in QP-based multiple manipulators cooperative control.

Chen and Zhang\textsuperscript{82} and Zhang et al.\textsuperscript{83} extend this method to motion control of mobile robot manipulator. In Zhang et al.,\textsuperscript{100} mutual collision avoidance of dual redundant robot manipulators is considered. In summary, application of QP-based method in multiple mobile robots have rarely developed and need the further investigation. In Li et al.,\textsuperscript{101} extend inequality-based collision avoidance method to multiple WMRs collision-free path following at the first time, which considered WMRs’ mutual collision avoidance except static or dynamic environmental obstacles. In above works introduced in this part, different technologies based neural network model are constructed for solving the resultant unified QP problem. Comparison on works based on constrained optimization method is shown in Table 3. Although they are effective, some parameters in controllers need to be adjusted manually based on the experimental requirement. How to set these parameters to derive the optimal performance or weaken effect of them on system performance are underway.

**Unmanned ground vehicles**

As a kind of the wheeled mobile robot, unmanned ground vehicles (UGVs) have been researching a lot in recent years. Safety is the basic requirement for UGVs. The reported safety accidents happened on UGVs in 2016, 2018 once increase people’s attention to safety. The safety driving problem of an off-road unmanned ground vehicle (UGV) is investigated in Chu et al.\textsuperscript{102} A local path-planning algorithm that utilizes directional information from the global route given by predefined way-points is designed, at the same time taking the influence of both the uncertainty of the environment and the vehicle dynamics into account. The proposed path-planning algorithm is performed on the autonomous vehicle A1, which win the 2010 Autonomous Vehicle Competition, illustrating that the two placed obstacles are successfully passed. Merely, positions of the encountered obstacles are assumed to be static. Autonomous driving in off-road environments requires
an exceptionally capable sensor system for obstacle perception. The fusion of stereo-vision and laser-range finder sensors are achieved in Hussein et al. for outdoor obstacles perception. Utilizing camera and lidar, an environment-detection-mapping method that is suitable for both rural and off-road environments is proposed in Choi et al. The algorithm consists of: lane, pedestrian-crossing, and speed-bump detection and obstacle detection gives a vision-based obstacle detection system for UGV in extreme environments.

The ability of obstacle circumvention in urgent situations is needed for UGV. Literature casts light on the coordinated steering and braking control of an UGV in emergency obstacle avoidance. In case of extreme emergency, the brake system of UGV will be in emergency braking to avoid collision. In this case, vehicle stabilization becomes important to ensure that the UGV does not lose control. However, stabilization actions may conflict with obstacle circumvention actions, so that potentially leading to a collision. The problem is solved in Funke et al., which mediates among these sometimes conflicting objectives by prioritizing collision avoidance.

Collision circumvention between UGV and pedestrian is a crucial issue that must be considered. Crossing Pedestrian Avoidance Guidance for UGV is investigated in Wu et al. A guidance method which can guide an UGV to follow a walking person along a collision-free path was proposed in Ku and Tsai. In emergency situations, human drivers universally incline to brake. In Fernandez Llorca et al., it suggests the use of automatic steering as a promising solution to avoid accidents. Moreover, this study designs a collision avoidance system

Table 3. Comparison on works based on constrained optimization method.

| Literatures | Robots type | Robots number | Collision avoidance | Problem description | Level | Mathematical formulation |
|-------------|-------------|---------------|---------------------|---------------------|-------|--------------------------|
| Xu et al.22 Zhang and Wang84,a | Manipulator | Single | Yes | Inequality | Velocity | Optimization |
| Zhang et al.83 | Mobile | Single | Yes | Inequality | Velocity | Optimization |
| Guo and Zhang86,b Li et al.89 | Manipulator | Single | Yes | Inequality | Acceleration | Optimization |
| Zhao et al.91,b Tang et al.94 | Manipulator | Multiple | No | Null | Null | Game-theory |
| Li et al.95 and Jin et al.96,97 | Manipulator | Single | Yes | Equality | Velocity | Optimization |
| Li et al.101,c | WMRs | Multiple | Yes | Inequality | Velocity | Optimization |

The difference between Xu et al.22 and Zhang and Wang84 is that the constructed controller. Lagrangian-based controller and dual neural network controller are proposed in Xu et al.22 and Wang84 respectively. In Guo and Zhang86, the inner and outer safe threshold is set. Literature91 gives the nearest point's coordinate of the manipulator distance from the obstacle. This is the first paper extended inequality-based collision avoidance method to multiple WMRs collision-free path following.
integrating pedestrian detection and circumvention for UGV. In order to avoid collision, it is beneficial to understand the intention of other road users such as pedestrians, and predict their next behavior. By collecting a large number of pedestrian crosswalk samples under various conditions and in different types of roads, analyzed pedestrian behavior from two different perspectives: the way they communicate with drivers prior to crossing and the factors that influence their behavior.

It is reported that it is needed 124 times human intervention for Google’s self-driving cars to clock 1,023,330 km proposes a data-driven augmented autonomous driving simulation system, which is useful to generate large amounts of training data to in-line to simulate the realistic UGVs. For this study, it requires very little human intervention. Merely, the specific quantity is not provided. In this part, we selectively review some obstacle circumvention works on UGV under off-road environment, emergency situation as well as pedestrian circumvention. In addition, an overview of motion planning for highway UGV is reviewed in Claussmann et al. Another overview can be found in Luettel et al., highlighting the common to most successful UGV systems as well as their differences. At present, several open source simulation platforms for UGV have been shared, such as Udacity, Carla, Apollo, etc. Baidu also shares ApolloScape Dataset for UGVs training and testing, including ApolloCar3D dataset and TrafficPredict dataset reported in Li et al.

Conclusion

In this paper, we selectively review the relevant literature on obstacle circumvention of wheeled mobile robots only with mobility in the last 20 years. APF-based, population-involved meta-heuristic-based, neural network-based, fuzzy logic-based, and constraint optimization-based collision avoidance methods are reviewed. We summarize the advantages and disadvantages of these methods in Table 4 for comparison. In summary, every kind of method has its advantages and disadvantages. For the original APF-based method, it is easy to understand due to the mathematical concept, together with the code implement, is simple. However, the method is easy to trap into the local minimum. In addition, the target will be non-reachable because the attractive force is less than the repulsive force when the obstacle is near the target. In terms of path optimality, the traveling path generated by the APF-based method is only a feasible path from the initial position to the target position. Although many variants are proposed, different potential functions are required for different scenes. Compared to the APF-based method, population-based meta-heuristic search method is able to generate the shortest path from the initial position to the target position. However, it requires a large memory compared to the ANN-based method. In terms of path generation, this class of meta-heuristic-based methods take a lot of time, and sized population is needed to obtain a desired result. ANN-based methods can learn, which can model linear, nonlinear, or complex relationships. Merely, compared to GA-based method, the ANN
method will fail in a highly chaotic environment. FL-based method can handle uncertainties and imprecise information using linguistic rules, and offer inference using environmental data. However, it is difficult to maintain the correctness, consistency, and completeness of a fuzzy rule base. Even for the recently popular QP-based optimization method, there are multiple control parameters that need to be adjusted manually in design of algorithm.

**Prospection**

The problem of obstacle circumvention has been a subject of consideration over the last decades but is still vivid and broadly investigated. This is because many problems have still been not solved even though many obstacle avoidance methods have been proposed. Obstacle avoidance methods should be chosen based on the specific requirements or criterion. For the moment, effective fusion of multiple obstacle avoidance methods is a promising method.
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References

1. Shitsukane A, Cheruiyot W, Otieno C, et al. A survey on obstacles avoidance mobile robot in static unknown environment. *Int J Comput* 2018; 28(1): 160–173.
2. Li S, Guo Y and Bingham B. Multi-robot cooperative control for monitoring and tracking dynamic plumes. In: IEEE International Conference on Robotics and Automation (ICRA), Hong Kong, China, 31 May–7 June 2014.
3. Jin L, Li S, Yu J, et al. Robot manipulator control using neural networks: a survey. *Neurocomputing* 2018; 285(12): 23–34.
4. Li X, Xu Z, Li S, et al. Cooperative kinematic control for multiple redundant manipulators under partially known information using recurrent neural network. *IEEE Access* 2020; 8: 40029–40038.
5. Gao X, Li J, Fan L, et al. Review of wheeled mobile robots’ navigation problems and application prospects in agriculture. *IEEE Access* 2018; 6: 49248–49268.
6. Vannoy J and Xiao J. Real-time adaptive motion planning (ramp) of mobile manipulators in dynamic environments with unforeseen changes. *IEEE Trans Robot* 2008; 24(5): 1199–1212.
7. Wu X, Liu J, Huang C, et al. 3-d path following of helical microswimmers with an adaptive orientation compensation model. *IEEE Trans Autom Sci Eng* 2020; 17(2): 823–832.
8. Xu T, Guan Y, Liu J, et al. Image-based visual servoing of helical microswimmers for planar path following. *IEEE Trans Autom Sci Eng* 2020; 17(1): 325–333.
9. Zhang Y, Li S and Liu X. Adaptive near-optimal control of uncertain systems with application to underactuated surface vessels. *IEEE Trans Control Syst Technol* 2018; 26(4): 1204–1218.
10. Zhang Y, Chen S, Li S, et al. Adaptive projection neural network for kinematic control of redundant manipulators with unknown physical parameters. *IEEE Trans Ind Electron* 2018; 65(6): 4909–4920.
11. Mohanan MG and Salgaonkar A. Probabilistic approach to robot motion planning in dynamic environments. 2020; 1(3): 1–16.
12. Gangadharan MM and Salgaonkar A. Ant colony optimization and firefly algorithms for robotic motion planning in dynamic environments. Eng Rep 2020; 2(3): e12132.
13. Aeberhard M, Schlichtharle S, Kaempchen N, et al. Track-to-track fusion with asynchronous sensors using information matrix fusion for surround environment perception. IEEE Trans Intell Transp Syst 2012; 13(4): 1717–1726.
14. Suhr JK, Jang J, Min D, et al. Sensor fusion-based low-cost vehicle localization system for complex urban environments. IEEE Trans Intell Transp Syst 2017; 18(5): 1078–1086.
15. Liu H, Yu Y, Sun F, et al. Visual–tactile fusion for object recognition. IEEE Trans Autom Sci Eng 2017; 14(2): 996–1008.
16. Sifuentes E, Casas O and Pallas-Areny R. Wireless magnetic sensor node for vehicle detection with optical wake-up. IEEE Sens J 2011; 11(8): 1669–1676.
17. Falanga D, Kim S and Scaramuzza D. How fast is too fast? The role of perception latency in high-speed sense and avoid. IEEE Robot Autom Lett 2019; 4(2): 1884–1891.
18. Mourikis AI and Roumeliotis SI. A multi-state constraint kalman filter for vision-aided inertial navigation. In: 2007 International Conference on Robotics and Automation (ICRA), Roma, Italy, 10–14 April 2007, pp.3565–3572.
19. Forster C, Pizzoli M and Scaramuzza D. SVO: fast semi-direct monocular visual odometry. In: 2014 International Conference on Robotics and Automation (ICRA), Hong Kong, China, 31 May–1 June 2014, pp.15–22.
20. Vidal AR, Rebecq H, Horstschaefer T, et al. Ultimate slam? Combining events, images, and IMU for robust visual SLAM in HDR and high-speed scenarios. IEEE Robot Autom Lett 2018; 3: 994–1001.
21. Gloye A, Simon M, Egorova A, et al. Predicting away robot control latency. In: Robot Soccer World Cup. Berlin: Springer, pp.712–719.
22. Xu Z, Zhou X and Li S. Deep recurrent neural networks based obstacle avoidance control for redundant manipulators. Front Neurorobot 2019; 13: 47.
23. Xu Z, Li S, Zhou X, et al. Dynamic neural networks for motion-force control of redundant manipulators: an optimization perspective. IEEE Trans Ind Electron 2021; 68(2): 1525–1536.
24. Khatib O. Real-time obstacle avoidance for manipulators and mobile robots. Int J Rob Res 1986; 5(1): 90–98.
25. Park MG, Jeon JH and Lee MC. Obstacle avoidance for mobile robots using artificial potential field approach with simulated annealing. In: 2001 IEEE International Symposium on Industrial Electronics (ISIE), Pusan, Korea, 12–16 June 2001, vol. 3, pp.1530–1535.
26. Shi E, Cai T, He C, et al. Study of the new method for improving artificial potential field in mobile robot obstacle avoidance. In: IEEE International Conference on Automation and Logistics (ICAL), Jinan, China, 18–21 August 2007, pp.282–286.
27. Tang L, Dian S, Gu G, et al. A novel potential field method for obstacle avoidance and path planning of mobile robot. In: IEEE international conference on computer science and information technology, Bradford, UK, 29 June–1 July 2010, vol. 9, pp.633–637.
28. Li H, Wang Z and Ou Y. Obstacle avoidance of manipulators based on improved artificial potential field method. In: 2019 IEEE international conference on Robotics and Biomimetics (ROBIO), Dali, China, 6–8 December 2019, pp.564–569.
29. Li G, Yamashita A, Asama H, et al. An efficient improved artificial potential field based regression search method for robot path planning. In: 2012 International Conference on Mechatronics and Automation (ICMA), Sichuan, China, 5–8 August 2012, pp.1227–1232.
30. Azhar A and Bilal Kadri M. Empirical evaluation of formation control scheme based on artificial potential fields for a team of nonholonomic mobile robots. In: 2018 International Conference on Emerging Technologies (ICET), Islamabad, Pakistan, 21–22 November 2018, pp.1–5.
31. Yang S, Bai W, Li T, et al. Neural-network-based formation control with collision, obstacle avoidance and connectivity maintenance for a class of second-order nonlinear multi-agent systems. *Neurocomputing* 2021; 439: 243–255.
32. Li B, Chang J and Wu C. A potential function and artificial neural network for path planning in dynamic environments based on self-reconfigurable mobile robot system. In: 2012 IEEE international symposium on Safety, Security, and Rescue Robotics (SSRR), College Station, TX, 5–8 November 2012, pp.1–6.
33. Kulic D and Croft EA. Real-time safety for human–robot interaction. *Robot Auton Syst* 2006; 54(1): 1–12.
34. Lacevic B, Rocco P and Zanchettin AM. Safety assessment and control of robotic manipulators using danger field. *IEEE Trans Robot* 2013; 29(5): 1257–1270.
35. Jing XJ and Wang YC. Artificial coordinating field based coordinating collision avoidance. In: 2003 *IEEE international conference on robotics, intelligent systems and signal processing*, Hunan, China, 8–13 October 2003, vol. 1, pp.126–130.
36. Shuai F, Xin L and Nan S. Research on multi-robot formation based on the artificial coordinating field. In: *International conference on computational and information sciences*, Chongqing China, 17–19 August 2012, pp.102–105.
37. Mirjalili S and Lewis A. The whale optimization algorithm. *Adv Eng Softw* 2016; 95: 51–67.
38. Kala R, Shukla A, Tiwari R, et al. Mobile robot navigation control in moving obstacle environment using genetic algorithm, artificial neural networks and a* algorithm. In: 2009 *Wri World Congress on Computer Science and Information Engineering (CSIE)*, Los Angeles, CA, 31 March–2 April 2009, pp.705–713.
39. Elhoseny M, Shehab A and Yuan X. Optimizing robot path in dynamic environments using genetic algorithm and bezier curve. *J Intell Fuzzy Syst* 2017; 33(4): 2305–2316.
40. Gao M, Xu J, Tian J, et al. Path planning for mobile robot based on chaos genetic algorithm. In: *International conference on natural computation*, Jinan, China, 18–20 October 2008, vol. 4, pp.409–413.
41. Zhang Zhang Y and Zhang X. Mobile robot path planning base on the hybrid genetic algorithm in unknown environment. In: 2008 *International conference on Intelligent Systems Design and Applications (ISDA)*, Kaohsiung, Taiwan, 26–28 November 2008, vol. 2, pp.661–665.
42. Shi P and Cui Y. Dynamic path planning for mobile robot based on genetic algorithm in unknown environment. In: 2010 *IEEE international conference on Chinese Control and Decision Conference (CCDC)*, Xuzhou, China, 26–28 May 2010, pp.4325–4329.
43. Wang B, Li S, Guo J, et al. Car-like mobile robot path planning in rough terrain using multi-objective particle swarm optimization algorithm. *Neurocomputing* 2018; 282: 42–51.
44. Dadgar M, Jafari S and Hamzeh A. A pso-based multi-robot cooperation method for target searching in unknown environments. *Neurocomputing* 2016; 177: 62–74.
45. Das PK, Behera HS, Das S, et al. A hybrid improved pso-dv algorithm for multi-robot path planning in a clutter environment. *Neurocomputing* 2016; 207: 735–753.
46. Pandey A. Mobile robot navigation and obstacle avoidance techniques: a review. *Int J Robot Autom* 2017; 2(3): 1–12.
47. Jiang X and Li S. Bas: beetle antennae search algorithm for optimization problems. *International Journal of Robotics and Control* 2018; 1(1): 1.

48. Khan AH, Li S and Luo X. Obstacle avoidance and tracking control of redundant robotic manipulator: An RNN-based metaheuristic approach. *IEEE Trans Ind Inform* 2020; 16(7): 4670–4680.

49. Peng G, Yang C, He W, et al. Force sensorless admittance control with neural learning for robots with actuator saturation. *IEEE Trans Ind Electron* 2020; 67(4): 3138–3148.

50. Zarate LE, Becker M, Garrido BDM, et al. An artificial neural network structure able to obstacle avoidance behavior used in mobile robots. In: *IEEE 2002 28th annual conference of the industrial electronics society*, Sevilla, Spain, 5–8 November 2002, vol. 3, pp.2457–2461.

51. Hu S, Cao C and Pan J. Deep-learned pedestrian avoidance policy for robot navigation. In: 2017 *IEEE international conference on Robotics and Biomimetics (ROBIO)*, Macau, China, 5–8 December 2017, pp.338–343.

52. Guan W, Weng Z and Zhang J. Obstacle avoidance path planning for manipulator based on variable-step artificial potential method. In: 2015 *IEEE international conference on Chinese Control and Decision Conference (CCDC)*, Qingdao, China, 23–25 May 2015, pp.4325–4329.

53. Huang BQ, Cao GY and Guo M. Reinforcement learning neural network to the problem of autonomous mobile robot obstacle avoidance. In: 2005 *International conference on machine learning and cybernetics*, Guangzhou, China, 8–21 August 2005, vol. 1, pp.85–89.

54. Qu H, Yang SX, Willms AR, et al. Real-time robot path planning based on a modified pulse-coupled neural network model. *IEEE Trans Neural Netw* 2009; 20(11): 1724–1739.

55. Wang X, Hou ZG, Zou A, et al. A behavior controller based on spiking neural networks for mobile robots. *Neurocomputing* 2008; 71(4–6): 655–666.

56. Wang X, Hou ZG, Lv F, et al. Mobile robots: modular navigation controller using spiking neural networks. *Neurocomputing* 2014; 134: 230–238.

57. Li H, Yang SX and Seto ML. Neural network based path planning for a multi-robot system with moving obstacles. *IEEE Trans Syst Man Cybern Part C* 2009; 39(4): 410–419.

58. Dierks T and Jagannathan S. Neural network control of mobile robot formations using rise feedback. *IEEE Trans Syst Man Cybern B* 2009; 39(2): 332–347.

59. Yu J, Ji J, Miao Z, et al. Neural network-based region reaching formation control for multi-robot systems in obstacle environment. *Neurocomputing* 2019; 333: 11–21.

60. Guo Y, Zhou J, Li G, et al. Robust formation tracking and collision avoidance for uncertain nonlinear multi-agent systems subjected to heterogeneous communication delays. *Neurocomputing* 2020; 395: 107–116.

61. Wang D, Deng H and Pan Z. Mrcdrl: multi-robot coordination with deep reinforcement learning. *Neurocomputing* 2020; 406: 68–76.

62. Silver D, Huang A, Maddison CJ, et al. Mastering the game of go with deep neural networks and tree search. *Nature* 2016; 529: 484–489.

63. Silver D, Schrittwieser J, Simonyan K, et al. Mastering the game of go without human knowledge. *Nature* 2017; 550(7676): 354–359.

64. Huang H, Yang C and Chen CLP. Optimal robot-environment interaction under broad fuzzy neural adaptive control. *IEEE Trans Cybern* 2021; 51: 3824–3835.

65. Huang H, Zhang T, Yang C, et al. Motor learning and generalization using broad learning adaptive neural control. *IEEE Trans Ind Electron* 2020; 67(10): 8608–8617.
66. Yang C, Chen C, He W, et al. Robot learning system based on adaptive neural control and dynamic movement primitives. *IEEE Trans Neural Netw Learn Syst* 2019; 30(3): 777–787.

67. Zeng C, Yang C, Cheng H, et al. Simultaneously encoding movement and sEMG-based stiffness for robotic skill learning. *IEEE Trans Ind Inform* 2021; 17(2): 1244–1252.

68. Yang C, Zeng C, Cong Y, et al. A learning framework of adaptive manipulative skills from human to robot. *IEEE Trans Ind Inform* 2019; 15(2): 1153–1161.

69. Wang N, Chen C and Nuovo AD. A framework of hybrid force/motion skills learning for robots. *IEEE Trans Cogn Dev Syst* 2021; 13: 162–170.

70. Yang C, Zeng C, Fang C, et al. A dmps-based framework for robot learning and generalization of humanlike variable impedance skills. *IEEE/ASME Trans Mechatron* 2018; 23(3): 1193–1203.

71. Zadeh LA. The concept of a linguistic variable and its application to approximate reasoning-III. *Inf Sci* 1975; 9(1): 43–80.

72. Song KT and Lin JY. Behavior fusion of robot navigation using a fuzzy neural network. In: *IEEE international conference on systems*, Taipei, Taiwan, 8–11 October 2006, vol. 6, pp.4910–4915.

73. Li H and Yang SX. A behavior-based mobile robot with a visual landmark-recognition system. *IEEE/ASME Trans Mechatron* 2003; 8(3): 390–400.

74. Faisal M, Hedjar R, Al Sulaiman M, et al. Fuzzy logic navigation and obstacle avoidance by a mobile robot in an unknown dynamic environment. *Int J Adv Robot Syst* 2013; 10(1): 37–271.

75. Wen S. Elman fuzzy adaptive control for obstacle avoidance of mobile robots using hybrid force/position incorporation. *IEEE Trans Syst Man Cybern C* 2012; 42(4): 603–608.

76. Yang H, Fan X, Shi P, et al. Nonlinear control for tracking and obstacle avoidance of a wheeled mobile robot with nonholonomic constraint. *IEEE Trans Control Syst Technol* 2016; 24(2): 741–746.

77. Zhu A and Yang SX. Neurofuzzy-based approach to mobile robot navigation in unknown environments. *IEEE Trans Syst Man Cybern C* 2007; 37(4): 610–621.

78. Ye C, Yung NHC and Wang D. A fuzzy controller with supervised learning assisted reinforcement learning algorithm for obstacle avoidance. *IEEE Trans Syst Man Cybern B* 2003; 33(1): 17–27.

79. Pandey A. Multiple mobile robots navigation and obstacle avoidance using minimum rule based ANFIS network controller in the cluttered environment. *Int J Adv Robot Autom* 2016; 1(1): 1–11.

80. Parhi DR, Pradhan SK, Panda AK, et al. The stable and precise motion control for multiple mobile robots. *Appl Soft Comput* 2009; 9(2): 477–487.

81. Pradhan SK, Parhi DR and Panda AK. Fuzzy logic techniques for navigation of several mobile robots. *Appl Soft Comput* 2009; 9: 290–304.

82. Chen D and Zhang Y. Robust zeroing neural-dynamics and its time-varying disturbances suppression model applied to mobile robot manipulators. *IEEE Trans Neural Netw Learn Syst* 2018; 29(9): 4385–4397.

83. Zhang Z, Chen S, Xie J, et al. Two hybrid multiobjective motion planning schemes synthesized by recurrent neural networks for wheeled mobile robot manipulators. *IEEE Trans Syst Man Cybern Syst* 2021; 51: 3270–3281.

84. Zhang Y and Wang J. Obstacle avoidance for kinematically redundant manipulators using a dual neural network. *IEEE Trans Syst Man Cybern B* 2004; 34(1): 752–759.
85. Guo D and Zhang Y. A new inequality-based obstacle-avoidance mvn scheme and its application to redundant robot manipulators. *IEEE Trans Syst Man Cybern C* 2012; 42(6): 1326–1340.

86. Guo D and Zhang Y. Acceleration-level inequality-based man scheme for obstacle avoidance of redundant robot manipulators. *IEEE Trans Ind Electron* 2014; 61(12): 6903–6914.

87. Zhang Y, Li S, Kadry S, et al. Recurrent neural network for kinematic control of redundant manipulators with periodic input disturbance and physical constraints. *IEEE Trans Cybern* 2019; 49(12): 4194–4205.

88. Zhang Y, Wang J and Xia Y. A dual neural network for redundancy resolution of kinematically redundant manipulators subject to joint limits and joint velocity limits. *IEEE Trans Neural Netw* 2003; 14(3): 658–667.

89. Li S, He J, Li Y and et al.; He J. Distributed recurrent neural networks for cooperative control of manipulators: a game-theoretic perspective. *IEEE Trans Neural Netw Learn Syst* 2017; 28(2): 415–426.

90. Chen D and Zhang Y. A hybrid multi-objective scheme applied to redundant robot manipulators. *IEEE Trans Autom Sci Eng* 2017; 14(3): 1337–1350.

91. Zhao W, Li X, Chen X, et al. Bi-criteria acceleration level obstacle avoidance of redundant manipulator. *Front Neurorobot* 2020; 14: 54.

92. Guo D and Li K. Acceleration-level obstacle-avoidance scheme for motion planning of redundant robot manipulators. In: *2016 IEEE international conference on Robotics and Biomimetics (ROBIO)*, Qingdao, China, 3–7 December 2016, pp.1313–1318.

93. Guo D, Feng Q and Cai J. Acceleration-level obstacle avoidance of redundant manipulators. *IEEE Access* 2019; 7: 183040–183048.

94. Tang WS, Lam CML and Wang J. Kinematic control and obstacle avoidance for redundant robot manipulators using a recurrent neural network. In: *International Conference on Artificial Neural Network (ICANN)*, Vienna, Austria, 21–25 August 2001, pp.922–929.

95. Li S, Chen S, Liu B, et al. Decentralized kinematic control of a class of redundant manipulators using recurrent neural networks. *Neurocomputing* 2012; 91: 1–10.

96. Jin L, Li S, Hu B, et al. Dynamic neural networks aided distributed cooperative control of manipulators capable of different performance indices. *Neurocomputing* 2018; 291: 50–58.

97. Jin L, Li S, Luo X, et al. Neural dynamics for cooperative control of redundant robot manipulators. *IEEE Trans Ind Inform* 2018; 14(9): 3812–3821.

98. Jin L, Li S, Xiao L, et al. Cooperative motion generation in a distributed network of redundant robot manipulators with noises. *IEEE Trans Syst Man Cybern Syst* 2018; 48(10): 1715–1724.

99. Chen D, Li S, Wu Q, et al. New disturbance rejection constraint for redundant robot manipulators: an optimization perspective. *IEEE Trans Ind Inform* 2020; 16(4): 2221–2232.

100. Zhang Z, Zheng L, Chen Z, et al. Mutual-collision-avoidance scheme synthesized by neural networks for dual redundant robot manipulators executing cooperative tasks. *IEEE Trans Neural Netw Learn Syst* 2021; 32: 1052–1066.

101. Li X, Xu Z, Li S, et al. Simultaneous obstacle avoidance and target tracking of multiple wheeled mobile robots with certified safety. *IEEE Trans Cybern* Epub ahead of print 7 May 2021. DOI: 10.1109/tcyb.2021.3070385
102. Chu K, Lee M and Sunwoo M. Local path planning for off-road autonomous driving with avoidance of static obstacles. *IEEE Trans Intell Transp Syst* 2012; 13(4): 1599–1616.

103. Caraffi C, Cattani S and Grisleri P. Off-road path and obstacle detection using decision networks and stereo vision. *IEEE Trans Intell Transp Syst* 2007; 8(4): 607–618.

104. Hussein A, Marin-Plaza P, Martin D, et al. Autonomous off-road navigation using stereo-vision and laser-rangefinder fusion for outdoor obstacles detection. In: 2016 *International conference on Intelligent Vehicles Symposium (IV)*, Gothenburg, Sweden, 19–22 June 2016, pp.104–109.

105. Choi J, Lee J, Kim D, et al. Environment-detection-and-mapping algorithm for autonomous driving in rural or off-road environment. *IEEE Trans Intell Transp Syst* 2012; 13(2): 974–982.

106. Guo J, Hu P and Wang R. Nonlinear coordinated steering and braking control of vision-based autonomous vehicles in emergency obstacle avoidance. *IEEE Trans Intell Transp Syst* 2016; 17(11): 3230–3240.

107. Funke J, Brown M, Erlien SM, et al. Collision avoidance and stabilization for autonomous vehicles in emergency scenarios. *IEEE Trans Control Syst Technol* 2017; 25(4): 1204–1216.

108. Wu W, Jia H, Luo Q, et al. Dynamic path planning for autonomous driving on branch streets with crossing pedestrian avoidance guidance. *IEEE Access* 2019; 7(99): 144720–144731.

109. Ku CH and Tsai WH. Obstacle avoidance in person following for vision-based autonomous land vehicle guidance using vehicle location estimation and quadratic pattern classifier. *IEEE Trans Ind Electron* 2001; 48(1): 205–215.

110. Fernandez Llorca D, Milanes V, Parra Alonso I, et al. Autonomous pedestrian collision avoidance using a fuzzy steering controller. *IEEE Trans Intell Transp Syst* 2011; 12(2): 390–401.

111. Rasouli A, Kotseruba I and Tsotsos JK. Understanding pedestrian behavior in complex traffic scenes. *IEEE Trans Intell Vehicles* 2018; 3(1): 61–70.

112. Li W, Pan CW, Zhang R, et al. AADS: augmented autonomous driving simulation using data-driven algorithms. *Sci Robot* 2019; 4(28): eaaw0863.

113. Claussmann L, Revilloud M, Gruyer D, et al. A review of motion planning for highway autonomous driving. *IEEE Trans Intell Transp Syst* 2020; 21(5): 1826–1848.

114. Luettel T, Himmelsbach M and Wuensche HJ. Autonomous ground vehicles—concepts and a path to the future. *Proc IEEE* 2012; 100(Special Centennial Issue): 1831–1839.

115. Virgo M. A self-driving car simulator built with unity, https://github.com/udacity/self-driving-car-sim (accessed 16 September 2012).

116. Puig MG. Open-source simulator for autonomous driving research, https://github.com/carla-simulator/carla (accessed 23 December 2020).

117. Jiaming L. An open autonomous driving platform: Apollo, https://github.com/ApolloAuto/apollo (accessed 22 September 2020).

118. ApolloScape. ApolloScape: Advanced open tools and datasets for autonomous driving, http://apolloscape.auto/index.html (accessed March 2018)

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