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Mobile robot navigation and obstacle avoidance techniques: A review

Abstract

Mobile robot is an autonomous agent capable of navigating intelligently anywhere using sensor-actuator control techniques. The applications of the autonomous mobile robot in many fields such as industry, space, defence and transportation, and other social sectors are growing day by day. The mobile robot performs many tasks such as rescue operation, patrolling, disaster relief, planetary exploration, and material handling, etc. Therefore, an intelligent mobile robot is required that could travel autonomously in various static and dynamic environments. Several techniques have been applied by the various researchers for mobile robot navigation and obstacle avoidance. The present article focuses on the study of the intelligent navigation techniques, which are capable of navigating a mobile robot autonomously in static as well as dynamic environments.

Keywords: mobile robot, sensor, actuator, navigation, obstacle avoidance

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Abbreviations: GA, genetic algorithm; NN, neural networks; PSO, particle swarm optimization; PWM, pulse width modulation; RNW-PSO, random inertia weight particle swarm optimization; ANN, artificial neural network; FL, fuzzy logic; Gas, Genetic Algorithms; MOGA, multiple objective genetic algorithm; SAA, simulated annealing algorithm; ACO, ant colony optimization; MPSO, modified particle swarm optimization; PSO, particle swarm optimization; RAOFC, reinforcement ant optimized fuzzy controller.

Introduction

This article introduces the literature survey of the various techniques used for mobile robot navigation. Navigation and obstacle avoidance are one of the fundamental problems in mobile robotics, which are being solved by the various researchers in the past two decades. The aim of navigation is to search an optimal or suboptimal path from the start point to the goal point with obstacle avoidance competence. Basically, the mobile robot navigation has been done by the Deterministic algorithm and Nondeterministic (Stochastic) algorithm. Nowadays, the hybridization of both the algorithms called as an Evolutionary algorithm is being used to solve the mobile robot navigation problem. Figure 1 shows the general classification of the Deterministic algorithm, Nondeterministic (Stochastic) algorithm, and Evolutionary algorithm, which are implemented for mobile robot navigation by various authors.

Navigation is an essential task in the field of mobile robotics, which can be classified into two types: global navigation and local navigation.[1] In the global navigation, the prior knowledge of the environment should be available. Many methods have been developed for global navigation, i.e. Voronoi graph,[2,3] Artificial potential field method,[4,5] Dijkstra algorithm,[6] Visibility graph,[7] Grids,[8] and Cell decomposition method,[9] and so on. In the local navigation, the robot can decide or control its motion and orientation autonomously using equipped sensors such as ultrasonic range finder sensors, sharp infrared range sensors, and vision (camera) sensors, etc. Fuzzy logic,[10] Neural network,[11] Neuro-fuzzy,[12] Genetic algorithm,[13] Particle swarm optimization algorithm,[14] Ant colony optimization algorithm,[15] and Simulated annealing algorithm,[16] etc. are successfully employed by various researchers to solve the local navigation problem. Rest of the article is organized as follows: Section 2 presents the literature survey of kinematic and dynamic analysis of the wheeled mobile robots. Section 3 discusses the literature review of various soft computing techniques used for mobile robot navigation. Finally, Section 4 describes the summary of this literature survey.

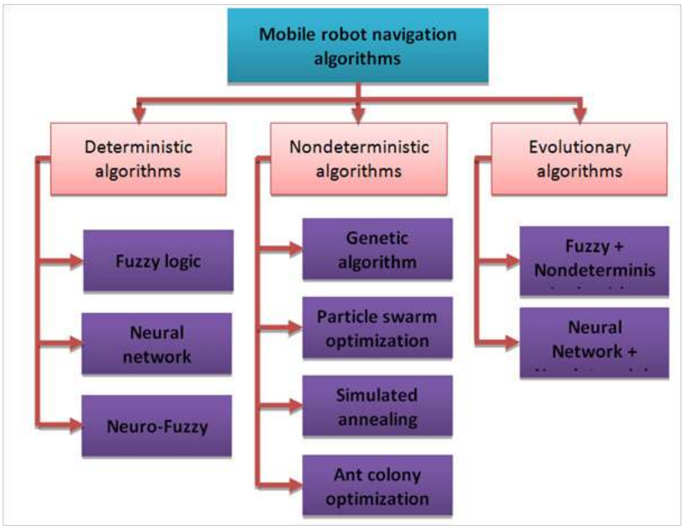

Figure 1 General classification of the Deterministic algorithm, Nondeterministic (Stochastic) algorithm, and Evolutionary algorithm used for mobile robot navigation.

Study of kinematic and dynamic analysis of the wheeled mobile robot

The motion control problem of an autonomous wheeled mobile robot has been widely investigated in past decades. In recent years, there has been a growing interest in the design and development of an autonomous wheeled mobile robot using various soft computing techniques. In Hui,[17] the authors have studied the kinematic and dynamic constraints of a car-like mobile robot and applied it to navigation among moving obstacles in the environments using neuro-fuzzy approaches. Abadi & Khooban[18] have solved the trajectory tracking problem of nonholonomic wheeled mobile robots using Random Inertia Weight Particle Swarm Optimization (RNW-PSO) based optimal Mamdani-type fuzzy controller. The motion problem of the wheeled mobile robots on uneven terrain has been addressed in Chakraborty.[19] Wang & Yang[20] have developed the neuro-fuzzy controller for navigation of a nonholonomic differential drive mobile robot. The combination of four sharp infrared sensors is equipped on the robot to read the obstacle distance, and this distance information is fed to the controller to adjust the speed of two separate motors of the robot. Wheeled mobile robots[21] have been widely used in various industrial applications, transportation, and social sectors, etc. Martinez et al.[22] have designed the kinematics and dynamics trajectory tracking control of the autonomous unicycle mobile robot using type-2 fuzzy logic and genetic algorithms. An adaptive neural network based motion and orientation control of a nonholonomic wheeled mobile robot has been presented in Al-Arajii.[23] Liang et al.[24] have presented the kinematic modelling of the two-wheeled differential drive mobile robot.

Various soft computing techniques used for mobile robot navigation

In the past few years, many soft computing techniques are proposed by the researchers to solve the robot navigation and obstacle avoidance problem in the various environments. The various soft computing techniques applied for mobile robot navigation in the different static and dynamic environments are summarized below.

Fuzzy logic technique for mobile robot navigation

The concept of fuzzy logic has been introduced by Zadeh,[25] which is extensively used in many engineering applications such as mobile robotics, image processing, etc. This method plays a vital role in the field of mobile robots. The fuzzy logic technique has been successfully applied by many researchers to control the position and orientation of mobile robot in the environment. Ren et al.[26] have designed an intelligent fuzzy logic controller to solve the navigation problem of wheeled mobile robot in an unknown and changing environment. Fuzzy logic systems are inspired by human reasoning, which works based on perception. In Yousfi,[27] the authors have presented the Gradient method based optimal Takagi-Sugeno fuzzy controller to tune the membership function parameters, and applied it to mobile robot navigation and obstacle avoidance. Qing-yong et al.[28] have presented the behavior-based fuzzy architecture for mobile robot navigation in unknown environments. They have designed four basic behaviours: goal-seeking behavior, obstacle avoidance behavior, tracking behavior, etc. for mobile robot navigation and tested it in various simulation environments. The eight rule-based fuzzy controllers have been designed by Boubertakh et al.[29] for obstacle avoidance and goal-seeking behavior of the mobile robot. Muthu et al.[30] have presented the Atmega microcontroller based fuzzy logic controller for the wheeled mobile robot. The proposed controller train the mobile robot to navigate in an environment without any human intervention. The controller receives inputs (obstacle distance) from the group of sensors to control the right and left motor of the mobile robot.

The sensor-based mobile robot navigation in an indoor environment using a fuzzy logic controller has been discussed.[31,32] Wu et al.[33] have developed the sensor based mobile robot navigation in the narrow environment using fuzzy controller and genetic algorithm. Where the fuzzy controller provides the initial membership function and the genetic algorithm choose the best membership value to optimize the fuzzy controller for mobile robot navigation. Obstacle avoidance is very important for successful navigation of autonomous mobile robot. Samsudin et al.[34] have combined the reinforcement learning method and genetic algorithm to optimize the fuzzy controller for improving their performance when the mobile robot moves in an unknown environment. Fuzzy reinforcement learning sensor-based mobile robot navigation has been presented by Beom & Cho[35] for complex environments. Pradhan et al.[36] have used fuzzy logic controller with different membership functions for the navigation of one thousand robots in an entirely unknown environment. The authors have compared the performance of different membership functions such as triangular, trapezoidal and gaussian for mobile robot navigation and stated that the gaussian membership function is more efficient for navigation. In Liu,[37] the authors have combined the fuzzy genetic algorithm to solve the path planning and control problem of an autonomous mobile robot (AMR) using ultrasonic range finder sensor information. Farooq et al.[38] have presented the comparative study between the zero order Takagi-Sugeno and Mamdani-type fuzzy logic models for mobile robot navigation and obstacle avoidance. Both the controllers receive inputs (obstacle distance) from the left and right ultrasonic sensors to control the left and right velocities of the motors of the mobile robot. During comparison study, the authors have found that in terms of smoothness Mamdani-type fuzzy model gives a better result. On the other hand, the Takagi-Sugeno fuzzy model takes less memory space in the real-time microcontroller implementation.

Hybridization of fuzzy and nondeterministic algorithm

Algabri et al.[39] have combined the fuzzy logic with other soft computing techniques such as Genetic Algorithm (GA), Neural Networks (NN), and Particle Swarm Optimization (PSO) to optimize the membership function parameters of the fuzzy controller for improving the navigation performance of mobile robot. They have designed two basic fuzzy logic behaviors: Motion to target behavior (MFLC) and obstacle avoidance behavior (AFLC). In Hiu,[40] the authors have developed genetic-fuzzy and genetic-neural for an adaptive navigation planning of a car-like mobile robot between dynamic obstacles. In this study, the genetic algorithm is employed to adjust the fuzzy membership function and weight of the neural network. Fuzzy PWM (Pulse Width Modulation) controller has been presented in the article[41] for mobile robot navigation and obstacle avoidance in an unknown environment. Abdessemed et al.[42] have designed an evolutionary algorithm to optimize the antecedent and consequent parameters of the fuzzy controller, and implemented it for mobile robot path planning. Selekwa et al.[43] have presented the fuzzy behavior controller for mobile robot navigation in the densely obstacle populated environments. The authors have designed two behavior control actions for navigation, namely obstacle avoidance behavior and the goal-seeking behavior. The obstacle avoidance behavior is done by range finding sensors, which detects the nearest obstacle distance, and the goal-seeking behavior is made by compass measurements, which determines the direction of the goal. Pratihar et al.[44] have developed a genetic-fuzzy technique based on a combined approach of genetic algorithm and fuzzy logic (GA-FL) to solve the mobile robot motion planning problems in the dynamic environments. Sensor-based wireless fuzzy controller has been designed by Faisal et al.[45] for mobile robot navigation in the industries among the static and dynamic objects. The two fuzzy controllers: tracking fuzzy logic control (TFLC) and obstacle avoidance fuzzy logic control (OAFLC) are helping the robot to search collision free path from the start point to goal point. Babalou & Seifiour [46] have developed the sensor-based on-line path planning method for the mobile robot in dynamic environments. Li et al. [47] have designed the four types of fuzzy controller: wall-following fuzzy, corner control fuzzy, garage-parking fuzzy and parallel-parking fuzzy for the car-like mobile robot

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(CLMR). The developed fuzzy controllers have been implemented real-time using field-programmable gate array (FPGA) chip, and tested it in various experimental scenarios. Li & Chang[48] have presented a real-time fuzzy target tracking control scheme for autonomous mobile robots using infrared sensors. The behavior-based fuzzy logic controller has been made by Dongshu et al.[49] to solve the navigation problem of mobile robot in unknown dynamic environment. The different fuzzy rule-based controller has been constructed to deal with different behavior and also helps the robot to get out from the trapped situations. Antonelli et al.[50] have presented the path-following approach for differential drive mobile robots using the fuzzy logic technique. The designed fuzzy rules are able to emulate the human driving behavior. Ayari et al.[51] have developed a multi-agent fuzzy logic intelligent control system, which trains the robot to navigate autonomously in dynamic and uncertain environments.

Neural network technique for mobile robot navigation

The neural network is one of the important technique for the mobile robot navigation. This neural network technique is motivated from the human brain, which is being applied by many researchers in the different fields such as signal and image processing, pattern recognition, mobile robot path planning, and business, etc. Zou et al.[52] have presented the literature survey of neural networks and its applications in mobile robotics. In Xiao,[53] the authors have combined the multi-layer feed forward artificial neural network with Q-reinforcement learning method to construct a robust path-planning algorithm for the mobile robot. Rai & Rai[54] have designed the Arduino Uno microcontroller-based DC motor speed control system using the Multilayer neural network controller and Proportional Integral Derivative (PID) controller. Patino & Carelli[55] have designed the automatic steering controller for a mobile vehicle using neural network architecture. Yang & Meng[56] have applied the biologically inspired neural network to generate a collision-free path in a nonstationary environment. Biologically inspired neural network based wall-following mobile robot has been presented by Nichols et al.[57] Online path planning between unknown obstacles in the environment is an interesting problem in the field of mobile robotics. Motlagh et al.[58] have presented the target seeking, and obstacle avoidance behaviours using neural networks and reinforcement learning. Mobile robot navigation using hybrid neural network has been addressed by Gavrilov & Lee.[59] Singh & Parhi[60] have designed multilayer feed forward neural network, which controls the steering angle of the robot autonomously in the static and dynamic environments. The different obstacle distances are the inputs of the four-layered neural network, and the steering angle is the output. Real-time collision-free path planning becomes more difficult when the robot is moving in a dynamic and unstructured environment.

Hybridization of neural network and nondeterministic algorithm

Rossomando & Soria[61] have designed an adaptive neural network PID controller to solve the trajectory tracking control problem of a mobile robot. Al-Jarrah et al.[62] have described the path planning and coordination of multiple mobile robots using probabilistic neuro-fuzzy architecture. The authors have applied leader-followers concept to control their position and orientation in the working environment, where the follower robots behave like a leader robot. This proposed probabilistic neuro-fuzzy architecture is the combination of first order Sugeno fuzzy inference model and Adaptive Neuro-Fuzzy Inference System (ANFIS). The fuzzy model has been used to control the linear and angular velocities of the leader robot and the follower robots, and ANFIS is implemented for automatic rule generation from the numerical dataset. In Janglova,[63] the author has presented a neural network-based technique for intelligent path planning and control of a mobile robot. The two neural network controllers are applied to path planning and control. The first neural network controller helps the robot to search free space in the environment, and the second neural network controller trains the robot for obstacle avoidance. Glasius et al.[64] have used Hopfield neural network for path planning and obstacle avoidance in the complex environment. In Kin,[65] the authors have proposed type-2 fuzzy neural network (IT2FNN) to solve the obstacle avoidance and position stabilization problems of wheeled mobile robots. IT2FNN consists of three layers: input layer, hidden layers, and output layer. This proposed IT2FNN has four inputs: distance between the robot and goal point, distance between the robot and nearest obstacle, goal angle, and obstacle angle. The outputs of the IT2FNN are linear and angular velocities of the robot. Mahmud et al.[66] have presented the vision (camera) sensor based Kohonen-type artificial neural network for intelligent navigation of mobile robot. Chohra et al.[67] have designed intelligent autonomous navigation structure for a vehicle using multi-layered neural networks (NN). Brahmi et al.[68] have solved the path planning and localization problem of mobile robot using recurrent neural network (RNN). This RNN allows the robot to navigate autonomously in the unknown environments. In Yang,[69] the authors have controlled the torque dynamic of nonholonomic mobile robot using neural network architecture.

Neuro-fuzzy technique for mobile robot navigation

Zhu & Yang[12] have presented a neuro-fuzzy sensor based reactive navigation of mobile robots in unknown environments. Forty-eight Fuzzy rules and two behaviours, target seeking, and obstacle avoidance are designed using this model. A neural network based learning techniques is developed to tune the parameters of membership functions, which reduces the navigation path length from a start position to the end position in an environment. Al Mutib & Mattar[70] have proposed the sensor-based navigation of mobile robot using neuro-fuzzy architecture. The authors have used eight ultrasonic range finder sensors for surrounding obstacle detection as the input of the neuro-fuzzy controller for selecting the correct left and the right wheel speeds for a mobile robot. Godjevac & Steele[71] have integrated the Takagi-Sugeno type fuzzy controller and Radial basis function neural network (RBFNN) to solve the mobile robot path planning. Where, the fuzzy logic is used to handle the uncertainty of the environment, and the neural network is used to tune the parameters of membership functions. In Li,[72] the authors have constructed behaviour-based neuro-fuzzy control architecture for a mobile robot navigation in an unstructured environment. The neural network is used to train the robot to reach the goal, and fuzzy architecture is integrated with it to control the velocities of the robot.

Joshi & Zaveri[73] have developed a neuro-fuzzy system for reactive navigation and control of a mobile robot in the environment with the presence of static and dynamic obstacles. Marichal et al.[74] have designed a neuro-fuzzy sensor-actuator control technique to steer the mobile robot in unknown environments. RAM based neuro-fuzzy approach for mobile robot navigation has been presented by Zhang et al.[75] They have used the fuzzy rule-based controller to interpret sensory information, and neural network controls the heading angle of the robot during navigation. Baturone et al.[76] have designed a low-cost embedded neuro-fuzzy controller for navigation of car-like mobile robot between the obstacles. Ma et al.[77] have used mixed soft computing techniques like fuzzy inference system and neural network to improve the learning and decision-making speed of a robot in

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unknown environments. Imen et al.[78] have applied the Adaptive Neuro-Fuzzy Inference System (ANFIS) technique to solve the path tracking problem of the nonholonomic wheeled mobile robots. They have used gradient descent learning algorithm to adjust the membership function parameters of the ANFIS. In Ganapathy,[79] the authors have designed the two controllers: a Fuzzy Logic (FL) controller for obstacle avoidance and Artificial Neural Network (ANN) for wall-following of the mobile robot. Both the controllers receive inputs from the different sensors to avoid the obstacles when the robot moves towards the desired goal. Zhao & Wang[80] have incorporated sonar sensors with the neural network to solve the navigation problem of the autonomous mobile robot.

Kumar & Dhama et al.[81] have integrated the neural network and fuzzy logic to control the motion and orientation of the mobile robot in the crowded unknown environment. In their work, the authors have used fuzzy rule-based and neural network for goal reaching and actuator control, respectively. Song et al.[82] have designed a heuristic fuzzy-neuro network to create a mapping between the ultrasonic sensor data and velocity command of the robot. They have used sixteen rules to control the direction of the mobile robot. In Lee,[83] the authors have developed a Takagi-Sugeno type recurrent neuro fuzzy system and hybrid algorithm (genetic algorithm with particle swarm optimization) to improve the path tracking stability of the mobile robots. The neuro-fuzzy systems have been classified into two categories:[84] adaptive neuro-fuzzy systems (ANFIS) and hybrid neuro-fuzzy systems. Deshpande & Bhosale[84] have discussed the navigation of a nonholonomic wheeled mobile robot using ANFIS controller. Rusu & Petriu et al.[85] have presented a sensor-based neuro-fuzzy controller for mobile robot navigation in indoor environments. They have used infrared and contact sensors for target seeking and obstacle avoidance behavior. Pothal & Parhi[86] have proposed a sensor based adaptive neuro-fuzzy inference controller for navigation of single and multiple mobile robots in the highly cluttered environment. The authors have designed control architecture, which is able to avoid obstacle autonomously in various situations and reach the target efficiently. Neural network integrated fuzzy controller has been designed by Ng & Trivedi[87] for mobile robot navigation and wall-following control. In their work, the authors have used only five rules to control the steering angle, heading direction, and speed of the robot during wall-following. Demirli & Khoshnejad[88] have developed sensor-based neuro-fuzzy controller for autonomous parallel parking of a car-like mobile robot (CLMR). The proposed model received data from the sonar sensors to control the turning angle of CLMR. Al-Mayyahi et al.[89] have applied ANFIS technique for autonomous ground vehicle (AGV) navigation. In this work, they have designed four ANFIS controllers to control the left and right angular velocities, and angle between the robot and target (heading angle). In Pradhan,[90] the authors have designed a navigational approach for multiple mobile robots using a neuro-fuzzy controller. The proposed controller receives input (obstacle distance) from the array of sensors to actuate the left and right wheel velocities of the mobile robots. Algabri et al.[91] have applied ANFIS controller for mobile robot navigation and obstacle avoidance in an unknown environment. The authors have presented many simulation tests using Khepera Simulator (KiKs).

Genetic algorithm for mobile robot navigation

Ghorbani et al.[13] have solved the global path planning problem of a mobile robot in the complex environment using genetic algorithm approach. Elshamli et al.[92] have presented a genetic algorithm technique for solving the path planning problem of a mobile robot in static and dynamic environments. Mohanta et al.[93] have designed Petri-GA technique to optimize the navigation path length of multiple mobile robots in the cluttered environment. Kubota et al.[94] have used the fuzzy controller to guide the mobile robot in a static and dynamic environment, and the conventional genetic algorithms (GAs) are integrated with it, to optimize the navigation path length. Tuncer & Yildirim[95] have proposed a new mutation operator for a genetic algorithm (GA) and applied it for mobile robot navigation in the dynamic environments. Moreover, the authors have tested their developed method in various simulation environments and compared it with traditional GA techniques and stated that their developed mutation operator based GA performs better over traditional GA. In Ming,[96] the authors have designed a genetic algorithm to choose the best membership parameters from the fuzzy inference system and implemented it to control the steering angle of a mobile robot in the partially unknown environment. Hu et al.[97] have designed the knowledge-based genetic algorithm for mobile robot navigation between U-shaped obstacle and maze environment.

Liu et al.[98] have presented the optimal path planning technique for a mobile robot using fuzzy logic and genetic algorithm. The fuzzy controllers are applied to modify the moving direction of the mobile robot according to the obstacle distance received from the sensors, and genetic algorithm is used to adjust and tune membership function and rules. Improved genetic algorithm based mobile robot navigation has been proposed by Li et al.[99] The authors have done many simulation tests in the both static and dynamic environments to show the effectiveness of the proposed algorithm. Qu et al.[100] have developed the improved genetic algorithm instead of a conventional genetic algorithm for global path planning of the multiple mobile robots. The advantages of the improved genetic algorithm are capable of guiding the mobile robots efficiently from the starting node to end node without any collision in the environment. In Algabri,[101] the authors have implemented Genetic-Fuzzy Controller (GA-FLC) to optimize and tune the Gaussian membership function parameters for mobile robot motion control. Castillo et al.[102] have designed Multiple Objective Genetic Algorithm (MOGA) for navigation path optimization of the mobile robot. Arora et al.[103] have presented the single fitness based genetic algorithm for solving the navigation problem in the dynamic environments. They have designed a fitness function based on the Euclidean distance formula between the robot and obstacle.

Simulated annealing algorithm for mobile robot navigation

The concept of simulated annealing algorithm has come from statistical mechanics.[104] The simulated annealing is an iterative search algorithm inspired by the annealing of metals.[105] Miao & Tian[16] have applied the heuristic method based simulated annealing algorithm for robot path planning in the dynamic environments. The authors have compared this proposed algorithm to the Dijkstra algorithm and stated that the proposed algorithm consumes less processing time to get a solution compared to Dijkstra algorithm. Sensor-based autonomous navigation of a mobile robot in the dynamic environment has been presented by Chang & Song.[106] Martinez-Alfaro et al.[107] have developed the simulated annealing and fuzzy logic for designing an automatic path planning technique for mobile robot. The simulated annealing algorithm is used to search a collision-free optimal trajectory between the fixed polygonal obstacles, and forty-nine fuzzy rules are applied to adjust the velocity of the robot during navigation. Zhu et al.[108] have presented the global path planning

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method for a mobile robot using Artificial Potential Field (APF) method and Simulated Annealing Algorithm (SAA). In Precup,[109] the authors have used SAA with fuzzy logic to adjust and optimize the antecedent and the consequent parameters of the fuzzy membership function and applied it to solve the optimization problem of the servo systems. Janabi-Sharifi & Vinke[110] have addressed the local and global navigation problems in the real environment using Artificial Potential Field method and Simulated Annealing Algorithm. Tavares et al.[111] have discussed the off-line path planning problem of a mobile robot using SAA. They have designed some adaptive tuning parameters to change the behavior of that algorithm. Due to the slow convergence rate of the conventional simulated annealing algorithm, the Liang & Xu[112] have presented a modified simulated annealing algorithm, and applied it to mobile robot global path planning.

Nakamura & Kehtarnavaz[113] have designed an optimal fuzzy logic controller for autonomous mobile robot navigation and hurdle avoidance using a genetic algorithm and SAA combinatorial optimization techniques. Hussein et al.[114] have designed three metaheuristic optimization algorithms: Tabu Search, Simulated Annealing and Genetic Algorithm; and implemented these algorithms to improve the navigation performance of mobile robot from the start point to goal point in an environment. Miao & Tian[115] have presented a simulated annealing algorithm based intelligent navigational controller, which helps the robot to search an optimal or near-optimal path in the static and dynamic environments. Zhang et al.[116] have combined the simulated annealing algorithm and Ant Colony Optimization (ACO) algorithm to increase the navigation speed of the mobile robot. In Gao,[117] the authors have improved the convergence speed of the simulated annealing algorithm using the artificial neural network and applied it to mobile robot path planning. Synodinos & Aspragathos[118] have integrated simulated annealing algorithm and artificial potential field method to rescue the robot from undesired local minima problem during navigation. Zhao & Zu[119] have developed a Modified Particle Swarm Optimization (MPSO) technique for mobile robot navigation in the dynamic environment.

Particle Swarm Optimization Algorithm for Mobile Robot Navigation

Particle swarm optimization (PSO) is a population-based stochastic algorithm, which is inspired by the social behavior of bird flocks. PSO algorithm is used to find an optimal or near optimal solution of the problem using fitness function $f(x) = f(x_1, x_2, x_3, ...x_n)$, where x_i is a population of the particles. Ahmadzadeh & Ghanavati[14] have presented the PSO algorithm based navigation method for multiple mobile robots. The robots move according to the global best (g-best) position of a particle in every iteration. To prepare an optimal intelligent controller for an autonomous wheeled mobile robot, the Castillo et al.[120] have designed the hybridization of an Ant Colony Optimization (ACO) algorithm and the Particle Swarm Optimization (PSO) algorithm to optimize the membership function of a fuzzy controller. Zhang et al.[121] have proposed the Multi-Objective Particle Swarm Optimization Algorithm (MOPSO) to search a collision-free optimal path in the uncertain dynamic environment. Zhang & Li[122] have presented a new objective function for mobile robot navigation using PSO. This objective function works based on the position of the obstacles and target in the environment. PSO algorithm has been successfully applied by Raja & Pugazhenthi[123] to optimize the travel time of the mobile robot in the dynamic environments. This algorithm searches the feasible path in the environment by randomly in every iteration. Masehian & Sedighizadeh[124] have solved the motion planning problem of the mobile robot by using multi-objective PSO.

PSO-based optimal fuzzy controller has been designed by Wong et al.[125] to determine the velocities of the left-wheeled motor and right-wheeled motor of the differential drive mobile robot. Specialized particle swarm optimization algorithm has been presented by Li et al.[126] for global optimum path planning of mobile robots. The authors have conducted many simulation tests in the simple and complicated environment to show the effectiveness of the proposed algorithm. Huang[127] has designed the Parallel Met heuristic Particle Swarm Optimization (PPSO) algorithm to solve the global path planning problem of an autonomous mobile robot. The author has implemented this PPSO algorithm in real-time using the field-programmable gate array (FPGA) chip. Chung et al.[128] have developed PSO and fuzzy based combinatorial algorithm to design intelligent navigation architecture for a mobile robot. They have used PSO algorithm to escape the robot from the dead-end condition, and the fuzzy algorithm is used to control the turn angle of a wheeled mobile robot during navigation and obstacle avoidance. Shiltagh & Jalal[129] have investigated the application of Modified Particle Swarm Optimization (MPSO) in the field of mobile robotics to determine a shortest feasible path from the beginning to end in an environment between obstacles. The developed modified PSO increases the convergence rate of the algorithms. Chatterjee & Matsuno[130] have solved the Simultaneous Localization and Mapping (SLAM) problem of mobile robots or vehicle using modified PSO and fuzzy evolutionary algorithm. Juang & Chang[131] have presented an evolutionary-group-based particle-swarm-optimization (EGPSO) for automatic learning of fuzzy system for mobile robot navigation or wall-following control in unknown environments. In Lu,[132] the authors have converted the robot path planning problem to the minimization problem and designed a fitness function based on the positions of the target and obstacles in the environment. Allawi & Abdalla[133] have proposed the sensor based PSO-fuzzy type-2 model for the navigation of multiple mobile robots. They have used PSO algorithm to determine the optimal input/output membership function parameters and rules for the fuzzy type-2 controller.

Ant colony optimization algorithm and other nondeterministic algorithms for mobile robot navigation

The Ant Colony Optimization (ACO) algorithm is used by many authors for mobile robot navigation and obstacle avoidance in the different environments. ACO is a probabilistic algorithm proposed by Dorigo et al.[134] in 1999, which is originated from bionics. Guan-Zheng et al.[135] have presented the modern global path planning method for a mobile robot by applying Ant Colony System (ACS) algorithm and the Dijkstra algorithm. Purian & Sadeghian[136] have explored the optimal path for a mobile robot in an unknown dynamic environment using Ant Colony Optimization (ACO) algorithm and fuzzy controller. This ACO algorithm searches the optimal value from the fuzzy rule table and minimizes the distance between the start points to goal point of the mobile robot with obstacle avoidance competence. Bi et al.[137] have designed an Ant Colony System (ACS) to improve the path searching speed of the mobile robot in the dynamic environment. Dong et al.[138] have presented an improved ACO algorithm for obstacle avoidance of mobile robot in the grid environment. In Ganapathy,[139] the authors have described various behaviours such as goal-seeking, wall-following obstacle avoidance for mobile robot navigation using improved ACO algorithm. Fan et al.[140] have applied an intensified ant colony optimization (ACO) algorithm to search an optimal path for

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mobile robot between irregular obstacles in an environment. Sariff & Buniyamin[141] have compared the performances of GA and ACO algorithm for robot path planning in the global static environment and stated that the ACO algorithm takes less time to search an optimal path in the environment compared to GA. Hsu et al.[142] have proposed an improved ant colony system algorithm by including a new pheromone updating parameter for path planning of mobile robots. Ganganath et al.[143] have designed an off-line path planner for nonholonomic mobile robots using an ACO algorithm. Juang & Hsu[144] have designed the reinforcement ant optimized fuzzy controller (RAOFC) and applied it for wheeled mobile robot wall-following control under reinforcement learning environments. The inputs of the proposed controller are range-finding sonar sensors, and the output is a robot steering angle. The antecedent and consequent parts of the fuzzy controller have aligned by the fuzzy type-2 clustering and ACO respectively.

Hsu & Juang[145] have designed the wall-following mobile robot using a type-2 fuzzy controller (IT2FC) and integrated it with an ACO algorithm to improve the performance of the controller. The steering angle and moving speed of the wall-following mobile robot has been controlled by two type-2 fuzzy controllers. In Juang,[146] the authors have presented the navigation method of the two robots (a leader robot and a follower robot) using fuzzy controllers (FC). They have applied continuous ant colony optimization and particle swarm optimization (AF-CACPSO) to the control the mobile robots to perform obstacle boundary following behavior. Hsu & Juang[147] have adopted the multi-objective ACO for optimized the rule parameters of the fuzzy controller (FC) for wall-following mobile robot. Chen et al.[148] have designed a scent pervasion (pheromone) principle of ant (ACO) based robotic path planning in a map environment. Hossain & Ferdousand[149] have applied Bacterial Foraging Optimization (BFO) method for mobile robot navigation to find out shortest possible path within the minimum time from the start position to the goal position between moving obstacles. Liang et al.[150] have developed a bacterial foraging algorithm for making a bio-inspired path planning strategy for a mobile robot. In the proposed model, the behavior of bacteria is applied to search an optimal collision-free path between the start nodes to the target node in an environment with obstacles. Brand & Yu[151] have applied the Firefly Algorithm (Glow-worm swarm optimization) to find a collision free shortest path in the two-dimensional static and dynamic environment for a mobile robot. They have compared this proposed algorithm to ACO algorithm and stated that the proposed algorithm provides better results (in terms of path length and computational cost) compared to ACO algorithm. Mohajer et al.[152] have presented a new Random Particle Optimization Algorithm (RPOA), which is inspired by the bacterial foraging technique, and used for local path planning for mobile robots in the dynamic and unknown environments. The proposed algorithm randomly searches the feasible path in the environment and avoids the moving obstacles by using the sensors. In Luo,[153] the authors have presented a review paper of multi-sensor fusion and integration and its application in the field of Mechatronic.

Summary

This article provides a literature survey of various techniques employed for mobile robot navigation. After summarizing the above literature review, the major conclusions are listed below:

a. The various soft computing techniques e.g. Deterministic, Nondeterministic, and Evolutionary algorithms, etc. have been applied by the researchers for mobile robot navigation and obstacle avoidance in the different environments.

b. According to literature survey, most of the researchers have used these soft computing techniques for mobile robot navigation and obstacle avoidance in only static environments. However, few researchers have considered dynamic environments for mobile robot navigation.

c. From the literature survey, it is observed that many researchers have demonstrated only computer simulation results without implementations of physical robot.

d. Nature-inspired algorithm based mobile robot navigation and obstacle avoidance is an important topic for the research. The hybridization of Deterministic and Nondeterministic algorithms is also a better choice for the research.

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Conflict of interest

Author declares that there is none of the conflicts.

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