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Discussion on different controllers used for the navigation of mobile robot

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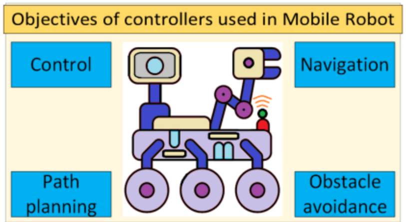
***Abstract*—Robots that can comprehend and navigate their surroundings independently on their own are considered intelligent mobile robots (MR). Using a sophisticated set of controllers, artificial intelligence (AI), deep learning (DL), machine learning (ML), sensors, and computation for navigation, MR's can understand and navigate around their environments without even being connected to a cabled source of power. Mobility and intelligence are fundamental drivers of autonomous robots that are intended for their planned operations. They are becoming popular in a variety of fields, including business, industry, healthcare, education, government, agriculture, military operations, and even domestic settings, to optimize everyday activities. We describe different controllers, including proportional integral derivative (PID) controllers, model predictive controllers (MPCs), fuzzy logic controllers (FLCs), and reinforcement learning controllers used in robotics science. The main objective of this article is to demonstrate a comprehensive idea and basic working principle of controllers utilized by mobile robots (MR) for navigation. This work thoroughly investigates several available books and literature to provide a better understanding of the navigation strategies taken by MR. Future research trends and possible challenges to optimizing the MR navigation system are also discussed.**

***Keywords*—artificial intelligence (AI); autonomous mobile robot (AMR); deep learning (DL); human-robot interaction (HRI); mobile robot (MR); machine learning (ML); PID controller**

I. Introduction

THERE are two types of ground robots generally in robotics science, stationary robots and mobile robots. Robots with fixed bases at a definite location are considered stationary robots and they have a limited workplace by the length of their linkages and the dynamic architecture. Despite stationary robots, those robots can move freely or autonomously in an unknown or predefined environment is considered as mobile robot and they have the unique ability to move independently inside a predetermined or variable environment to carry out specific operations and accomplish desired targets [1], [2]. With the continuous development in robotics science, nowadays robots are the most important part of national defense, the service sector, and industries. Demand for MR has increased recently due to its application in tough and dangerous tasks such as heavy object carriage, military surveillance, operations, and many more. The well-organized integration of hardware systems, vision, motion control, and decision-making establish robotic intelligence. Robust and accurate visual intelligence helps robots be intelligent and recognize their environment [3]. Moreover, mobile robots became autonomous and even more intelligent when AI was implemented into them. Today's MRs can navigate securely through complex environments, recognize natural language, recognize objects, track themselves, outline their own tracks, and usually think for themselves. Throughout the decades, mobile robots have made a significant contribution to modern society's well-being in a variety of fields, including commercial, retail, healthcare, and social domains [4]. The process of designing MRs uses the technologies and methodologies of behavior, intelligent, and cognitive-based control, and efforts to optimize the resiliency of performance dependent on minimum input datasets and minimum complexity of computation. Fig. 1 shows the illustration of controller's objective used in MR.

Fig. 1. Illustration of controller's objective in MR



MRs have gained a lot of fascination over the past decade because of their capacity to explore difficult and complex regions including space, perform search and rescue, and carry out activities that are not dependent on human intervention. MRs is defined as a device that can gather data from their surroundings and apply their understanding of their job to advance protection practically and importantly [5]. Generally, an MR is considered in the literature as a device that operates a cognitive link between perception and their corresponding action. MRs are becoming the essential technological driver of modern society because of the rapid advancement of automation, intelligence, and digitalization, and the market for applications for intelligent goods has continuously risen, which has also led more individuals to understand the relationship between intelligent objects and the latest techniques [6]. The field of control and navigation for MRs has attained over recent years higher achievements, both in experiments and theories. The remainder of this review paper is structured as follows.

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Section II introduces the literature survey of some important review or survey articles and books, Section-III describes the most important controllers such as PID controllers, and model predictive controllers, as well as rule-based systems such as fuzzy logic controllers (FLC) and reinforcement learning (RL) controllers, Section-IV provides a comprehensive discussion on controller's application and future trends, and Section-V describes conclusion.

II. LITERATURE SURVEY

Several state-of-the-art reviews, and survey articles from well-known journals, and books remain in the literature which extensively describes reviews of specific areas within the mobile robot (MR) field.

A. *State-of-the-Art, Review, and Survey Articles*

Many researchers have been working continuously to provide the best state-of-the-art articles having information about the MR in recent decades. Some of these articles are summarized here.

Rubio *et al*. [7] summarized and explored the idea of mobile robots including the new trends. Different types of mobile robots such as flying robots, legged robots, and wheeled mobile robots have been explained. This article discusses the role of new technologies such as AI, nanorobotics, cooperative work, human-robot interactions, perceptions, and many more in the development of different kinds of mobile robots. Robotics applications in numerous fields of applications such as industry, healthcare, medicine, distribution of goods, ergonomics, and service robots are illustrated in this paper.

Paden *et al.* [8] present a survey of the state-of-the-art algorithms for control and planning by keeping a specific focus on urban settings. This article analyzed different models of mobile vehicles used, in the contrast of architecture of predefined and unknown environments, and the requirements of various computation strategies. This survey helps to get a deeper insight into the limitations and strengths of available control and planning approaches for the navigation of mobile vehicles.

Kiumarsi *et al.* [9] present a comprehensive review of available feedback control solutions based on reinforcement learning (RL) to optimize tracking and regulations of multiagent and single systems. This study describes major algorithms such as RL and Q-learning algorithms for continuous-time (CT) and discrete-time (DT) systems, respectively. A novel approach to off-policy RL has been discussed for both CT and DT systems. Various applications of RL algorithms for navigation purposes are described.

Elbanhawi *et al.* [10] present a review paper on sampling-based planning of robotics motion. Some major proposed planners are estimated through simulation and underline some of the details of methodologies that are generally left undefined. This study addresses techniques that can tackle current problems in robot navigation and emphasizes future research probabilities. Optimal planning, planning under uncertainty, Kino-dynamic planning for real life, and replanning for dynamic environments are discussed.

Bresson *et al.* [11] proposed a survey on SLAM (Simultaneous Localization and Mapping) technology when considering current trends in autonomous driving. Firstly, the limitations of classical techniques in autonomous driving have been presented and then, major approaches are described to tackle these limitations. Various conditions such as season, weather forecast, etc., and different paradigms such as distributed, centralized, etc., for long-term planning of maps are considered. This paper discussed the remaining challenges and future research trends around the SLAM approach.

Chen *et al.* [12] present a brief description of the current advancements in robotics vision. Kalman filters resolve dilemmas in robot motion control, navigation, tracking, localization, following, visual manipulation, estimation and prediction, and reconstruction of structure from a set of gathered images. This article mostly described the different kinds of Kalman filters including unscented and extended Kalman filters, which are used nowadays for the autonomous navigation of robots.

Zhu *et al.* [13] illustrate Deep Reinforcement Learning (DRL) application for the navigation of MR. This work analyses the differences and relationship between major scenarios such as indoor navigation, social navigation, multi-robot navigation, and local obstacle avoidance, during the case of the DRL application for MR navigation. Also, some major developments, challenges, and their corresponding possible measures have been provided for DRL-based navigation.

Khan *et al.* [14] analyses of cooperative MR target tracking approaches. Some important control strategies for cooperative tracking, are cooperative search, tracking, and acquisition, cooperative multi-robot consideration of unstable targets, and avoiding multi-robot pursuit. This study recognizes the five biggest steps that characterize this issue, namely, the target, the environment, the robot, the coordination technique, and the used sensors. This systematic study is mainly focused on the observation of multi-target situations.

David *et al.* [15] provide a survey on the several control techniques developed over time for the backward direction motion of MR with trailers. A truck-trailer MR's ability to move in the backward direction is challenging since the whole system is extremely unstable and non-linear. This study describes the available literature in this area to recognize unsolved issues and challenges.

Mohan *et al.* [16] present an overview of available and possible research techniques in swarm robotics. Swarm robotics is a novel technique for coordinating multi-robot systems composed of many small, very basic robots that draw their concept from social insects. The potential of swarm robots is also discussed in this review to achieve a common goal for cooperative work. This article mainly focused on the existing algorithms, problems, and research shown in swarm robotics methodologies.

Haddadin *et al.* [17] explain the recognition, detection, and isolation of robotics collisions through the survey. For better HRI, reliable and fast handling of prospective collisions on the complete architecture of the robot is required, together with control techniques for risk-free robot reaction. The main objective behind this is to protect human beings from possible physical injuries. This study addresses the context-free stages of the event of collision sequence for robots dealing with surroundings, including HRI, and manipulating tasks. The issue is initially examined for static robots followed by expansion to incorporate transmission or joint flexibility.

B. *Some Major Books*

In recent decades, several researchers have been focusing on optimizing the potential of MR. Many researchers have been working continuously to provide the best state-of-the-art articles having information about the MR in recent decades. Some of these articles are summarized here in Table I.

TABLE I
SOME MOST IMPORTANT BOOKS ON INTELLIGENT MOBILE ROBOTS

Author	Title of the book	Year	Contents
Canny et al. [18]	Complexity of Robot Motion Planning	1988	• Analysis of robotics and algorithms • The roadmap algorithms, and motion constraints • Problems associated with robot motion planning. • Lower bounds in motion planning, and elimination theory.
Meystel et al. [19]	Autonomous Mobile Robots Vehicles with Cognitive Control	1991	• Intelligent motion control, the evolution of AMR • Basic theory of cognitive control, cognitive controller • Planner, Navigator, Pilot, Cartographers • Actuation control system, simulation, and testing
Borenstein et al. [20]	Navigating Mobile Robots: Systems and Techniques	1996	• State-of-the-art mobile robot navigation • Basic sensors, systems, methods, and technologies • Position measuring technologies including odometry, inertial navigation, and natural and artificial landmark recognition. • Comparing and analysis of different techniques for navigation
Jones et al. [21]	Mobile Robots: Inspiration to Implementation	1998	• Introduction and designing principle of MR. • TuteBot, computational hardware including relays, bump switches, and some discrete components. • Designing and prototyping, sensors, power sources, mechanics • Motors, robot programming and applications, robot projects
Nehmzow et al. [22]	Mobile Robotics: A Practical Introduction	2003	• Introduction of MR, and its hardware parts • Learning technologies, navigation strategy, and novelty detection • Simulation and modeling of robot and environment interactions • Study and analysis of robot’s behavior.
Cuesta et al. [23]	Intelligent Mobile Robot Navigation	2005	• Different control techniques • Fuzzy systems and stability analysis • Intelligent control of MR with Fuzzy perception, Fuzzy reactive navigation of MR • Adaptation of traditional electrical vehicles
Dudek et al. [24]	Computational Principles of Mobile Robotics	2010	• Describes algorithms related to several techniques for reasoning, sensing, and locomotion. • Focused on legged and wheeled MR. • Details of multi-robot systems and SLAM techniques • State-of-the-art for the computational principles of MR
Siegwart et al. [25]	Introduction to Autonomous Mobile Robots	2011	• Fundamentals of MR concepts about localization, motion planning, control theory, signal analysis, cognitive layers, and AI. • Hardware parts of MR include motor, sensory, and perceptual. • Description of software and hardware architecture • Computer vision, information theory, and probability theory
Juang et al. [26]	Intelligent Robots	2019	• Complex line tracking for the humanoid robots • Active vision communications between two humanoid robots using image recognition techniques. • Active speech communications between two MRs enable robots to understand human language and communicate. • Multi-target object recognition by humanoid robots with complex colors and a humanoid robot grabs steady objects.

III. SOME MAJOR CONTROLLERS

In the context of MRs, a controller is a device or system that receives sensor data and generates actuator commands to guide the robot's motion toward a desired behavior or goal. The controller is the most important part of the MR that falls in the control system, for navigation with higher efficiency and accuracy. The controller uses feedback from the robot's sensors to continuously adjust the actuator commands, to maintain a desired trajectory or achieve a specific task. MR control addresses the issue of finding out the amounts of torque and forces generated by the robot's controllers that need to be generated to enable the MR to move in an intended direction, follow an intended trajectory, and, generally, complete an action with the required performance standards. The inertia forces, coupled response actions, and gravitational impacts make controlling problems in MRs (fixed and dynamic) more challenging than normal. Both the transitional phase and the stable-state term are protected by the efficiency criteria. In surroundings that are well-defined and fixed, like factories, the surroundings can be set up to match the MRs characteristics. The specific type of controller used will depend on the application and the desired performance of the mobile robot. Overall, the goal of a controller in an MR is to enable the robot to autonomously navigate and perform tasks in dynamic and uncertain environments. Various types of controllers can be used in mobile robots, including feedback control systems such as PID controllers, and model predictive controllers (MPC), as well as rule-based systems such as FLCs and reinforcement learning controllers.

A. *PID Controllers*

A PID controller is a device employed in processes requiring control to govern process variables including speed, pressure, flow, and temperature. Proportional, integral, and derivative control make up the PID controller. All these controllers work together to provide a control plan to obtain control over the process. PID controllers, considered to be highly precise and reliable controllers, use a feedback system known as the control loop for controlling variables that impact the process. The most used control algorithm implemented in robotic systems is the PID controller. The usage of PID algorithms for control is almost exclusively necessary for high-end robots that have powerful dynamics and excellent mobility precision. MRs are made to carry out certain jobs in a challenging and hazardous environment. Because of this, it's crucial to proceed at a precise, accurate velocity that will be appropriate for the task itself and the surrounding circumstances [27]. Fig. 2 shows an algorithm for an MR control within a desired distance.

PID adaptation serves as a closed-loop algorithm and is frequently used in academic and industrial research due to its

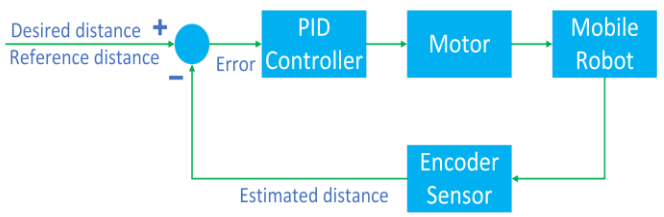

Fig. 2. PID controller for controlling a MR to a distance

simplicity and higher performance. The fundamental objective for feedback-controlled systems in MR is to minimize this signal of error, which represents the discrepancy between the calculated speed values and the speed of reference. In PID controllers: the main objective of the proportional operation is to provide a response that changes in proportion to the incorrect signals; the integral controller mitigates the regulatory mistakes generated by a proportional controller during operations; and the derivative controller is used to find the variations in estimated signal by utilizing proportional controller in the rate of fluctuation. PID controllers estimate the value of error as the variance between a calculated value of the operational variable and the expected value. The calculation for the tracking error provides a framework for the PID controller operations. The control action taken by the PID controller for MR navigation is denoted by u(t), which is abbreviated as equation 1.

$$u(t) = k_p e(t) + k_i \int_0^t e(t)\,dt + k_d \frac{de(t)}{dt} \quad (1)$$

Where proportional, integral, and derivative parameters are denoted by k_p, k_i, and k_d respectively. The time step is denoted by $e(t)$, where the controller regulates the signal of control proportionally to the errors. Some important PID controller-based MR navigation is described in Table II.

TABLE II
PID CONTROLLER-BASED MOBILE ROBOT NAVIGATION

Reference	Main Work
[28]	• A PID controller is used to solve the path-finding issues for MR. The model of MR is integrated with a delay and an integrator. • Here, the simple integration process enables the PID controller to be adjusted while using nominal effectiveness and reliability as control parameters.
[29]	• The development of the robotic fish and its movement control strategies are the objectives of this study. • A versatile anterior body and a vibrating foil acting as propellers have been employed to create a remote-controlled, four-linked analogous robotic fish. • The hybrid control technique and a PID control technique are used in the remote control of fish speed.
[30]	• A basic decentralized continuously sliding PID controller has been developed for navigation tasks that ensure semi-global robustness for each closed-loop signal and exponential convergence of monitoring faults. • Terminal attractants and saturating ones are considered, along with a dynamic sliding mode that has been imposed without reaching the stage. • This paper is supported by an experimental comparison against adaptive control, PID control, and PD control for a stiff robot hand.
[31]	• A novel dynamic architecture PID controller pattern method is used for monitoring and stabilizing robot movement. • This study validates the feasibility of an exact PID sliding controller and PID sliding surface in monitoring the manipulator of a robot. • The entire quadratic model of Lyapunov and both the lower and upper matrix standard inequality are used in this work to define the global and sliding stability specifications. • Using simulations, the suggested control algorithm in this study is implemented for a two-link direct-driven robot hand.
[32]	• The global asymptotic control of manipulators for robotics within input limitations is covered in this study, regardless of velocity data presence. • By applying LaSalle's invariance principle and Lyapunov's direct technique, it is demonstrated that a robotic system with limited inputs might be universally asymptotically stabilized using a highly saturated PID controller. • In this article, the indicated controller's features are discussed, including the shortage of modeling variables in the description of a control rule and the capability of assuring that actuator limitations are not violated.
[33]	• This study proposes a fuzzy-PID controller architecture for tracking the trajectory of an MR with a differential drive. • The fuzzy PID controller has three outputs and two inputs, and its design includes a fuzzy controller and a PID controller. • An MR with a differential drive is explained using a model depending on the Lagrange dynamic method. • For an MR with any variable beginning state, the recommended controller provides a greater rate of convergence than the traditional PID controller.

B. *Model Predictive Controllers*

A movable device that can navigate and communicate with its surroundings through its actuators and sensors is known as an MR. The difficulty of determining how to push to travel from one location to another along with how to complete an assigned task is an example that controllers for MR tackle. A modern control technique referred to as MPC (model predictive control) has the potential to generate optimal responses while taking the system's state and input constraints into consideration. To optimize the signal to control and anticipate possible breaches in the state trajectories while restricting the input signal within the acceptable range of standards, a dynamical system is implemented to determine how the state trajectories will evolve in the future [34]. MPC develops the control rule implicitly by resolving an optimization problem that can be constrained. Fig. 3 shows the role of MPC for MR navigation.

The receding horizon optimization control formulation is a key component of MPC. The best control series across a limited potential horizon for N steps can be determined at time t using

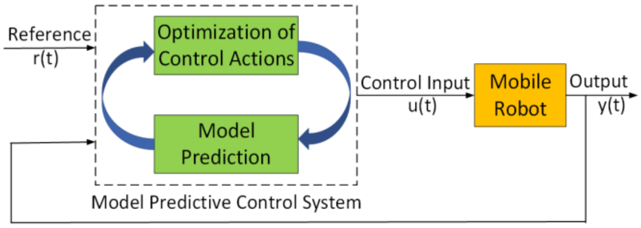

Fig. 3. Illustration of Model Predictive Controllers for Mobile Robots

this technique. The appropriate formulations have been presented below in Equation 2 [34]:

$$\min_{u_t,\dots,u_{t+N-1}} \left\{ \sum_{k=0}^{N-1} \left(\|y_{t+k} - r(t)\|^2 + \rho \|u_{t+k} - u_r(t)\|^2 \right) \right\} \quad (2)$$

Subject to:

$$x_{t+k+1} = f(x_{t+k}, u_{t+k})$$

$$y_{t+k} = g(x_{t+k}, u_{t+k})$$

$$u_{min} \leq u_{t+k} \leq u_{max}$$

$$y_{min} \leq y_{t+k} \leq y_{max}$$

$$x_t = x(t), k = 0, \dots\dots, N-1$$

We calculate the optimal series through N steps by applying the principle of the receding horizon, although we just use the initial component, the initial ideal control movement action $u^*(t)$. We continue the optimization at time $t+1$ using the latest information and state estimations. In general, we use feedback to improve the optimization throughout the time horizon chosen to estimate the prospective evolution of the system outcomes.

MPC can operate control systems that traditional feedback controllers are unable to control. The concept of optimum control under limitations and the basic structuring of control laws into an optimization issue have made MPC useful for a variety of work. The most significant difference between MPC and traditional control systems, which employ control principles that have already been computed, is the integration of optimization and prediction [35]. The present measurements and anticipated outcomes of the outputs serve as a base for the MPC computations. The goal of the MPC control computations is to select a series of control actions that will move the projected response to the reference or target value in the best possible manner [36]. Fig. 4 illustrates the single-input-single-output (SISO) control for MPC, where the manipulated input is u, and the projected output is y. The term "prediction horizon" refers to the range of predictions P, whereas "control horizon" refers to the range of control actions N.

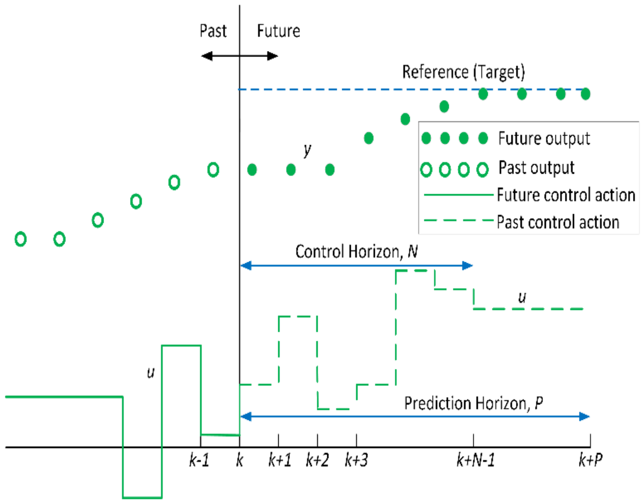

Fig. 4. Illustration of primary idea for Model Predictive Controllers [37]

The MPC approach determines an array of N values ranging from the input $\{u\ (k + j - 1), j = 1, 2, \dots\dots, N\}$, at the present sampling moment, represented by k. The array contains $N - 1$ anticipated inputs and the present input $u(k)$. Following the N control movements, the input is kept constant. The inputs are computed to ensure that an array of P anticipated outputs $\{y\ (k + j)$, *where*, $j = 1, 2, \dots, P\}$, attains the reference points through an optimal approach. An objective function is optimized in the control computations [37].

MPC delivers various significant advantages [37], [38], [39]: (1) the inputs, outputs, and disturbance parameters operate dynamically and statically for the process framework, (2) comprehensive assessment of the inputs and outputs constraint, (3) the acquisition of the best reference points might be connected to the control computations, and (4) a reliable model anticipates can provide preliminary indications of prospective issues. MPC is a useful control technique for MR navigation; however, there are still several unresolved challenges and opportunities for advancement. The computing complexity involved with addressing the optimization difficulty in real-time is a key constraint in MPC for MR navigation. Research might be focused on the development of more accurate optimization algorithms or estimations that can deliver real-time strategies, especially to address MRs with constrained handling features [40]. The development of MPC algorithms that will successfully rely on data from multiple sensors (including cameras, IMUs, and lidar) and perception methods (including object and character recognition) to enhance navigation performances can be an area for further study [41]. It becomes even more essential to generate MPC algorithms that optimize the planning paths and the efficiency of energy, specifically for MRs that utilize batteries. Some important MPC-based MR navigation is described in Table III.

TABLE III
MPC-BASED MOBILE ROBOT NAVIGATION

Reference	Used Technique	Main Work
[42]	Interactive MPC framework	• A system that anticipates the purposes of pedestrians and their engagement with groups and, consequently, depending on the prediction, MR searches for the perfect path. • The recommended approach provides safe, effective, and intuitive robot behaviors in the presence of crowded situations.
[43]	Perception-Aware MPC	• This framework uses numerical optimization to generate trajectories under the platform's spatial constraints that fulfill the framework's behavior and require inputs to control. • By increasing the extent of view of an object of focus and decreasing its rate of motion at the visual level, it optimizes awareness criteria for reliable and robust sensing during MR navigation.
[44]	Robust Constrained Learning-based Nonlinear MPC	• The outcome in this study shows a reliable, adaptive controller that, during initial testing whenever uncertainty about the model is substantial, offers safe, traditional control and eventually ends in higher-performance, optimum control over subsequent experiments, while model uncertainty decreases as experience rises.
[45]	DeepMPC	• This paper introduces DeepMPC, a remote real-time MPC technique developed to handle challenging tasks like automated food cutting, where dynamics can vary with external variables such as material and equipment category as well as with time.
[46]	Convex Quadratic Programming-Based MPC	• This work considers the collision-free movement of robotic automobiles using convex quadratic programming-based MPC. • Real-time prevention of collisions for a fully autonomous vehicle in dynamic as well as static conditions is made possible by a novel collision-free navigation mechanism presented.
[47]	Nonlinear MPC algorithm	• For the virtual motion planning and monitoring of an omnidirectional AMR, a nonlinear MPC technique is presented in this study. • A Hamiltonian minimization approach is used as the foundation of the technique to optimize the control route as determined using a cost function.

C. Fuzzy Logic Controllers

As AI technology quickly advances, robotics is becoming more sophisticated and effective in doing activities that were previously considered extremely challenging and complicated. MRs are capable of being autonomous, which means they can do tasks without human assistance by combining AI technology with robots [48]. To enhance the efficiency of MRs' reactive navigation, a variety of AI approaches, including RL, fuzzy logic, neural networks, and evolutionary algorithms, can be used. Fuzzy logic is an essential instrument in control systems because it can express linguistic words and make decisions reliably despite unpredictability and insufficient data. Fuzzy logic is applied for developing potential approaches to execute steering control, path planning, local navigation, global navigation, obstacle avoidance, and speed control for an MR. FLC is highly suited for operating MR due to its ability to make decisions even in the face of unpredictability and subsequently employs a collection of linguistically fuzzy rules to apply expert skills in a variety of circumstances [49].

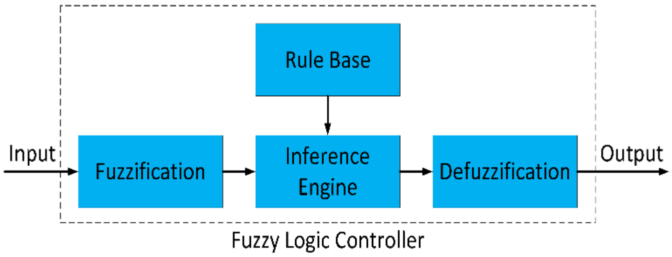

Fig. 5. Illustration of Fuzzy Logic Controllers architecture

The architecture of FLC is illustrated in Fig. 5. The Fuzzification, inference engine, rule base, and defuzzification are all four fundamental parts that collectively form the FLC, which are described below:

1) Fuzzification

Fuzzy sets are generated from raw inputs using this element. The fuzzy sets move through the control system to undergo additional processing. Fuzzification, which converts each actual value of input and outcome into degrees of participation in fuzzy regulation conditions, is the starting point of generating a fuzzy controller [50].

2) Inference Engine

This tool generates the most appropriate rules for specific inputs. The output is subsequently produced as a fuzzy output by applying these rules to the provided data. The fuzzy decision-making technique is carried out using fuzzy inference, that integrates the information obtained through the fuzzification [50]. Various fuzzy inference techniques exist according to a membership function objective and structure.

3) Rule Base

The functions of membership and rules that govern or control the fuzzy logic system's decision-making ability can be found within this component. It also includes the IF-THEN statements that can be employed to set up conditions and control the system.

4) Defuzzification

The fuzzy sets are converted into a precise output by this component. This is the final step for a fuzzy logic system and the purpose of this step is to interpret the outcomes that the inference engine determined in subgroups.

FLC uses a collection of linguistic fuzzy rules for using expert skills in a variety of scenarios. To avoid obstacles precisely and reach the destination while navigating through an environment having different shapes and sizes of obstacles, a controller based on fuzzy logic can be developed by describing or developing the input and output parameters, fuzzification, fuzzy logic system-based 'If-Then' fuzzy inference rules, and the defuzzification technique to enhance the mobility of MRs in coordination with obstacle placements [51]. The FLC can control both navigational instruction and obstacle avoidance tasks simultaneously. A fuzzy logic system (F_i $(i \in [n])$ is described in equation 3 [52], where the total number of inputs is n for the fuzzy logic controller.

$$F_i = \{(y_i, \mu_F(y_i)) \mid \mu_F(y_i) \in [0,1]\ \forall y_i \in \mathbb{R}\} \qquad (3)$$

Where the membership function is $\mu_F\!: y_i \to [0,1]$, and the following in equation 4 [52], is a convex triangular representation of it:

$$\mu_F(y_i) = \begin{cases} 0, & if\ y_i < b_1 \\ \mathcal{L} = \left(\frac{y_i - b_1}{b_2 - b_1}\right), & if\ y_i \in [b_1, b_2] \\ R = \left(\frac{b_2 - y_i}{b_3 - b_2}\right), & if\ y_i \in [b_2, b_3] \\ 0, & if\ y_i > b_3 \end{cases} \qquad (4)$$

Where $b_1 \leq b_2 \leq\ b_3$ as illustrated in Fig. 6-(a), and $\mathcal{L}(R)$ is a rigid decreasing (increasing) function in a predefined interval. Then, for a collection of predefined m-rules, and $Y \in \mathbb{R}, Y = (y_1, y_2)$, the j-th rule is abbreviated in equation 5 [52].

$$\lambda_j\ :\ If\ y_1\ is\ A_{j;1}\ \wedge\ y_2\ is\ A_{j;2} \to\ \varphi\ is\ B_j, \qquad (5)$$

Where B_j is a subsequent fuzzy system, $y_1 = s$ and $y_2 = \dot{s}$. Therefore, the fuzzy mapping for FLC is a function $\varphi\ :\ Y \to \mathbb{R}$, as given in Fig. 6-(b).

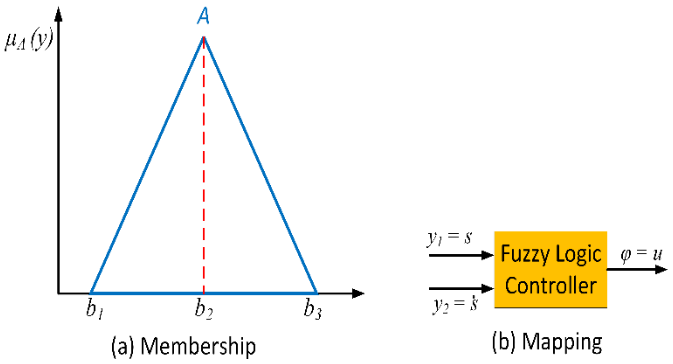

Fig. 6. (a) Illustration of the triangular membership function with a basic concept. (b) Illustration of the basic idea of mapping for the fuzzy logic controller [52]

The centroid defuzzification establishes a standard mapping in equations (6) and (7) [52]:

$$\varphi(Y) = \frac{\sum_{j=1}^{m} Z_j(Y).B_j}{\sum_{j=1}^{m} Z_j(Y)}, \qquad (6)$$

$$Z_j(Y) = \mu_{A_{j;1}}(y_1).\mu_{A_{j;2}}(y_2), \qquad (7)$$

Where φ represents the control signal u, and $Z_j(Y)$ represents the power of firing for the j-th rule for computed observation Y from the product t-normalization of membership function ($j \in [m]$).

In recent decades many researchers discovered various control strategies based on FLCs for the navigation of MR. Some important and famous controllers based on fuzzy logic controllers for the navigation of MR are described in Table IV.

TABLE IV
FUZZY LOGIC CONTROLLER-BASED MOBILE ROBOT NAVIGATION

Reference	Used Technique	Main Work
[53]	Hierarchical type-2 FLC	• For AMRs, a new reactive control framework is presented. • A type-2 hierarchical FLC is developed by combining the fundamental navigational behaviors and how they coordinate with each other. • The proposed control system can address the challenges that MRs face in unpredictable environments.
[54]	Behavior-based neuro-FLC	• This work describes a neuro-fuzzy control for indoor sensor-based navigation of MRs. • MR behaviors are organized in a sequence as a component of the control system.
[55]	Multilayer decision based FLC	• In this paper, the FLC uses the predictions and setting priorities criteria for a multilayer selection to enhance the performance of the subsequent position in terms of its runtime, safety, and path length. • The primary purpose of this research is to present a multilayer decision based FLC for understanding non-collision MR mobility in an unpredictable dynamic setting and find a strategy enabling MR navigation along a secure trajectory while avoiding all forms of obstacles.
[56]	Genetic-fuzzy approach	• Real-time prevention of collisions for a fully autonomous vehicle in dynamic as well as static conditions is made possible by a novel collision-free navigation mechanism presented. • The state parameters and set of rules in an FLC that an MR employs to move through dynamic obstacles are scaled up in this research using genetic algorithms.
[57]	Neuro-fuzzy Controller	• The neuro-fuzzy is utilized in this work for adjusting the fuzzy controller's output settings to enable the Khepera IV MR to navigate on a secure and effective path toward the target.

D. Reinforcement Learning Controllers

The traditional MR navigation system lacks the capacity for independent learning. MRs must have the ability to move independently over unknown terrain and avoid hitting dynamic and static obstacles. The navigation system of MRs has been developed through a variety of methods, both traditional and heuristic. When the environment becomes complicated, traditional methods can become tedious and might stop working at the local optimum. Heuristic techniques have grown in preference nowadays for their proximity to human styles of behavior learning [58]. RL is one of the most famous heuristic approaches that is used extensively nowadays for the navigation of MR. Using the RL method, MR can recognize the path through its prior behavior. For effective usage of an algorithm like this, the MR, also known as an agent, recognizes the environment, takes a decision, and subsequently is rewarded or penalized according to the environment. The MR then adjusts its strategy when it finally obtains a bigger reward. By developing a wide range of rules, the agent can learn several behavioral approaches [59].

RL has drawn substantial interest for its potential to address the basic challenge of navigation experienced by MRs, due to its powerful representations and experience-based learning capabilities. RL is an algorithm that finds the best decision-making techniques via experience and is influenced by how animals learn in psychology [60]. Any decision-maker is considered an agent in RL, and all that exists around the agent is known as the environment. The agent interacts with its surroundings to optimize the overall reward and receives a feedback signal as a reward quantity for the training [61], [62]. The Markov decision process (MDP) can be utilized to represent the link between the environment and the agent [13]. Even though the agent obtains immediate input on rewards for each time step, the aim of RL is to optimize a long-term collective value of rewards rather than temporary rewards. The reward value (R) at time t can be expressed as equation 8 by considering the discount factor $\lambda \in [0, 1]$ [13].

$$R_t = r_{t+1} + \lambda r_{t+2} + \lambda^2 r_{t+3} + \cdots = \sum_{k=0}^{\infty} \lambda^k r_{t+k+1} \qquad (8)$$

For the link between the environment and the target through the MDP, the state of the environment, obtained reward value, action taken by the agent, and the probability of state transition are represented by E, R, A, and P, respectively. The policy of agents π is the mapping of space between state and action elements. When the state of the environment $e_t \in E$, the actions $a_t \in A$ is taken by the agent and then goes to the subsequent environment state e_{t+1} according to the probability (P) of state transition, while receiving feedback for reward value $r_t \in R$ from the environment.

The state value function of the environment e_t is $V_\pi(e)$ and function for action value of the pair of state-action (e, a) is $Q_\pi(e, a)$. The long-term reward value that the agents might expect through the policy π can be calculated by equations 9 and 10 [13].

$$V\pi(e) = F_\pi[R_t | e_t = e] \qquad (9)$$

$$Q_\pi(e, a) = F_\pi[R_t | e_t = e, a_t = a] \qquad (10)$$

By using equations (8), (9), and (10) can be represented in equations (11) and (12), recursively to define the link between the states $e = e_t$ and $e' = e_{t+1}$ [13].

$$V\pi(e) = \sum_a \pi(e, a) \sum_{e'} P_{ee'}^a [R_{ee'}^a + \lambda V\pi(e')] \qquad (11)$$

$$Q\pi(e, a) = \sum_{e'} P_{ee'}^a [R_{ee'}^a + \lambda \sum_{e'} Q\pi(e', a')] \qquad (12)$$

Where $R_{ee'}^a = F[r_{t+1} | e_t = e, e_{t+1} = e', a_t = a]$ and $P_{ee'}^a = P[e_{t+1} = e' | e_t = e, a_t = a]$. Equations (11) and (12) are referred to as Bellman equations. Dynamic programming is used to get the estimated solutions for the Bellman equation with the current value function. By optimizing the value function, the agent subsequently enhances the policy π constantly.

As comprehensive dynamic data and enormous memory usage are required for dynamic programming, which is not possible, researchers have established two different methods for learning, including Temporal-Difference (TD) learning and Monte Carlo. The Q-learning technique was developed in [63] by integrating different theories, including MDP and the Bellman equations, with TD learning. Following that, RL technology has achieved tremendous advances, and RL techniques have been utilized to address a variety of real-world issues including MR navigation.

The classic RL technique, on the other hand, struggles with the so-called complexity of multidimensional scenarios, where the computing load significantly rises as the variety of inputs grows. Therefore, applying RL to develop a suitable policy in a vast state space is challenging. The DL technique learns the basic regulations and fundamental properties of the source data while modeling nonlinear functions via training a deep neural network (DNN). After combining RL with DNN, deep reinforcement learning (DRL) can be developed.

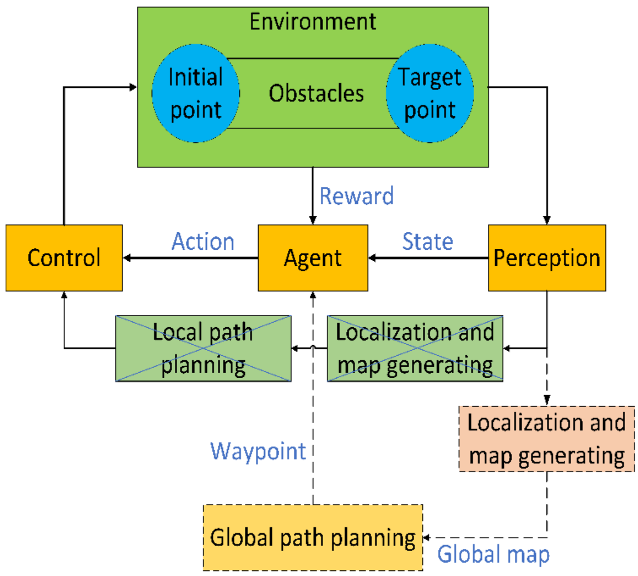

Fig. 7. Illustration of the DRL-based MR navigation [13]

Nowadays, several studies are using DRL-based MR navigation to supplement or replace the conventional navigation approach. The DRL-based navigation system's agent and environment interact with each other in Fig. 7. The localization and map-generating sections, along with the local path planning section, that comprise the conventional navigation system are replaced by the DRL agent, which moves in the direction of the target location while avoiding dynamic, static, and other obstacles. A sequence of waypoints is generated by the global path planning component in Fig. 7 to serve as intermediate points of reference during DRL-based MR navigation, allowing the combined system of navigation to execute extended-distance navigation across a complicated physical environment. Some important RL-based MR navigation systems have been discussed in Table V.

TABLE V
REINFORCEMENT LEARNING-BASED MOBILE ROBOT NAVIGATION

Reference	Used Technique	Main Work
[64]	Self-Supervised DRL	• This work suggests a universal computational graph that comprises value-driven model-free techniques and model-based techniques, with representations applying interpolation between model-based and model-free, designed to solve the requirement to learn complex policies with limited data.
[65]	Memory-based DRL	• The technology described in this study enables a quadrotor unmanned aerial vehicle (UAV) integrated with a monocular camera to automatically avoid obstacles in irregular and unexplored indoor spaces. • The main objective of this technique is the partial observability concept and technique for how UAVs keep safe the necessary information for the structure of the environment to achieve greater navigation decision-making for the future.
[66]	Inverse RL	• This study provides an innovative technique for simulating human behavior in navigation coordination. • This research uses a mixed distribution to represent the MRs behavior, intending to adjust for both the discrete navigational choices—such as whether to turn left or right—and the inherent variability of human paths. • The recommended method can mimic pedestrian behavior as well as recreate a particular behavior that is instructed via teleoperation within MR's target environment.
[67]	Supervised learning assisted RL algorithm	• A hybrid coarse and fine learning process for a neural fuzzy system is suggested. • The function of membership for both input and output parameters are found concurrently using supervised learning. • When fine learning is used, the function memberships for output parameters are adjusted using an RL technique. • In this work, the MR can perform collision-free navigation.
[68]	Graph Relational RL	• The challenge of autonomous navigation in substantial landscapes with dense static and moving objects is considered in this study. • Results from simulations confirm the generalizability to other contexts and superior performance for earlier efforts in large-scale congested regions.

IV. DISCUSSION AND FUTURE TRENDS

MRs will be able to make decisions in real time using input from sensors and advanced goals due to the integration of the latest algorithms and ML techniques in future controllers. For an MR to navigate effectively and safely, controllers need to accurately incorporate input from various sensors, including cameras, ultrasonics, LiDAR, and many more, to gain awareness of their surroundings [69]. Thus, researchers will focus on the advancement and accuracy of sensors for further research. Prospective MR controllers might want to consider ethical and social conventions, mostly for situations where humans and robotics interact. Therefore, research will mainly focus on the development of navigation controllers that follow acceptable social behavior [70]. Future research trends will look at hybrid control structures that take advantage of both data-driven and rule-based control features. Another essential research path in the future is to examine how controllers in MR might utilize edge computing for instantaneous decision-making and cloud servers for challenging computations and the processing of huge amounts of data [71], [72].

MRs will increasingly involve cognitive architecture, AI, speech communication, and affective HRI through a variety of applications, including military security and defense, hazardous work, surveillance, advancing space exploration, hazardous environments, and so on [73], [74]. These technologies will further have an impact on a wide range of economic fields, including agriculture, health care, domestic services, undersea research, industry, and many more. MRs will be perfected to transform the home, distribution and logistics, marine research, and automobile industries. The application of MRs will have an expanding impact on the food and beverage sector, processing foods, pick-and-place usage, networking purposes, and collaborative tasks.

Technologies like linguistic intelligence, automatic driverless automobiles, delivery drones, and automated manufacturing facilities with MR as employees are currently having a significant impact on how companies perform. For future studies, various groups of objectives, such as motion consistency, multi-robot frameworks, sensor vibration, and several more, need to be taken into consideration. Real-world MR navigation regularly experiences uncertainty and sensor noises [75]. The most recent trend indicates that the commercialization of autonomous vehicles because of advances in technology in MRs will drive the economy over the period to come, while the rise of open-source systems combined with a decline in the cost of sensors is anticipated to boost the popularity of domestic MRs, including lawn mowers and vacuum cleaners.

V. CONCLUSION

The objective of this paper is to present an overview that allows a comprehensive understanding of controllers used for MR navigation while analyzing the available information. The different controllers are divided into classical and rule-based techniques in this study that are used in MR navigation. Also, we have illustrated the most important books that can be referenced as a base for the robotics field of study. Control, navigation, path planning, and obstacle avoidance are the core components of the study behind the application of controllers for MR. We provided a survey on different techniques utilized by the most cited articles, according to the IEEE Xplore and Google Scholar. The latest references are provided for readers who intend to delve into this area, and the state-of-the-art, innovative applications and further trends are dispersed throughout the article.

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